Collateral Constraint and China's Credit Boom in the Global Financial Crisis: Loan-level Anatomy *

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Abstract

Collateral is at the heart of modern financial system and plays an essential role in business cycles and financial cycles. Leveraging detailed loan level data covering a major city in China, the paper first provides stylized facts on bank loan collateral structure. It then shows that facing the tension between heightened uncertainty and government mandate of credit expansion during the GFC, banks significantly raise collateral requirements while shortening loan maturity. Pre-existing relationship helps in obtaining bank loans in normal times but has less bite during the GFC. As a further consequence, firms are forced to curb investment in intangible assets, resulting in less firm innovation. The anatomy of the collateral dynamics sheds light on how credit gets created and (mis) allocated during the GFC, and provides micro-level evidence for some recent salient macroeconomic facts on China.

Keywords: Collateral Constraint, Global Financial Crisis, Credit Boom, Bank Loan
JEL: G01, G21

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1 Introduction

Collateral is at the heart of modern economy and plays a critical role in financial cycles, business cycles, and resource misallocation (Geanakoplos, 2010; Kiyotaki and Moore, 1997; Midrigan and Xu, 2014). Despite significant developments on the theoretical front, empirical evidence and stylized facts are still lacking, and there are many open empirical questions such as, what are collateral patterns in loan contracts for emerging economies like China (given the crucial importance of bank loans for financing growth)? How do collateral requirements in bank loan contracts change over the business cycles ? What are the real consequences of the collateral dynamics?

China constitutes a unique setting to address these questions for the following reasons. First, in response to the global financial crisis (GFC, hereafter) shortly after the collapse of Lehman, Chinese government rolled out a massive economic stimulus package, including government spending plans (the "four trllion" stimulus) and credit expansion policies. Following the stimulus, there has been a dramatic surge in new bank loan issuance, as evidenced by panel A in figure 1 which presents the changes in the overall outstanding amount of bank loans. There was actually a great credit boom in China after the Lehman episode. The credit boom triggered by the GFC is the natural backdrop for the research. Second, like many emerging economies, China's credit markets are bank-centric and collateral plays a critical role in loan contracts. A study of the collateral structure can shed light on the credit creation and credit cycles of these economies. Third, to implement the stimulus package, Chinese banks (mostly state-controlled) face a big tension: on the one hand, it is an imperative to extend credit according to the policy mandate of the central government; on the other hand, the banks are concerned about default risks at a time of heightened uncertainty after Lehman collapsed. As a result, collateral constraint becomes more binding for credit expansion. To the extent that more efficient firms (mostly privates firms) may be more collateral-constrained, the credit boom may have led to massive misallocation. Lastly, given China's rising economic importance and the great transition in the past decades, understanding the nature of the dynamics of China's economy has crucial implications for China and the world as well.

Leveraging a proprietary bank loan contracts dataset, the paper aims to address the questions raised at the beginning. The sample covers all loans issued between 2006 and

2010 by one of the big four state-owned banks in China in a big city located in east China. In particular, the paper tries to achieve the following goals. First, we provide a set of stylized facts on the collateral dynamics of bank loans over the business cycle. Second, by linking loan-contract data and borrower-firm level data, we provide micro-evidence on how collateral structure and changing requirements affect credit creation and affects firms' real decisions. Finally, we try to account for some salient macroeconomic facts on China after the GFC: surging debts, housing boom, economic slowdown, and declining aggregate TFP and increasing dispersion of TFP across firms.

There are three features that make our dataset especially interesting. First, it covers a wide range of industries and thus is not limited to manufacturing firms. This allows us to explore more on the industry-wise heterogeneity. Second, the sample includes a large number of loans to small and medium firms. Most datasets focus on large and medium firms only and our data provides an opportunity to take a glance at the part of firms that are usually "missing". Last but not least, it provides details on the underlying collateral. Previous researches mostly rely on Chinese Annual Survey of Industry Enterprises which is essentially a survey on large and medium manufacturing firms, or the Chinese Banking Regulatory Commission loan-level dataset that covers mostly large firm with no information on loan rate and collateral (Hau and Ouyang, 2018; Huang et al., 2020; Cong et al., 2019). The unique features of our sample allow us to explore the collateral structure in Chinese bank loans and see how it responds to the credit expansion during the GFC.

We first report several stylized facts on the Chinese bank loan collateral structure. Overall, earnings-based (unsecured and guaranteed loans) and asset-based loans (mortgage and pledge loans) are about equal in terms of volume. [1] Mortgage loans constitute the largest (39.09%) among the four types of loans. What's more, the composition of collateral structure is significantly related to certain firm characteristics. Highly rated, large or medium sized SOEs borrow more unsecured. Lower-rated, large or medium sized firms, regardless of ownership structure, obtain more guaranteed loans. Mortgage loans are for small non-SOEs of all ratings and pledge loans are the most detached from firm features.

[1] Unsecured loans are completely backed by borrower's creditworthiness. Guaranteed loans requires further credit enhancing through guarantees provided by third parties. Mortgage (diya) loans and pledge (zhiya) loans are backed by assets. This difference lies in the actual delivery of the asset from the borrower to the lender, which is necessary only in the case of pledge loans. Section 2.4 introduces the four types of loans in detail.

We then further explore how the loan structure responds to the credit expansion during the GFC. Using the outstanding volume of each type of loans at quarter-ends, we find that mortgage and pledge loans increase while guaranteed loans drop as compared to unsecured loans during the credit expansion in China. The collateral structure analyses further confirm the shift from earnings-based loans to asset-based loans. Post the credit expansion, the outstanding volume share of mortgage loans rises by 3.8% while that for unsecured and guaranteed loans drop by 0.7% and 2.8%, respectively. During the crisis, despite easing monetary policy, firm's future prospects become more uncertain and future earnings are hard to predict. The guarantee from third-party is not as reliable during the financial crisis as before given that the guarantors may also be exposed to the shock. Rising agency costs makes it less appealing to lend earnings based loans. In this case, the provision of collateral adds better protection to the loan in the case of borrower default. Thus, we would observe unsecured and guaranteed loans making way for asset-based loans such as mortgage and pledge loans.

The baseline findings are consistent with bank's raising collateral requirements while expanding credit under high economic uncertainty. We then provide some robustness checks and heterogeneity analysis. First, the major identification challenge for researches that focus on the impacts of credit supply is to isolate changes from credit supply and demand (Amiti and Weinstein, 2018). The Difference-in-Differences setting in volume analysis and the scaling by total loan volume should iron out the average change in firm credit demand. We also control for firm credit demand by including firm*time fixed effects following Khwaja and Mian (2008). Second, we exclude the possible impacts of varying firm composition by focusing on non-SOEs, large and medium sized firms, and high rating firms only. Third, there are contemporaneous policies such as the "Four trillion economic stimulus" that intentionally guide funding to specific industries. Our results remain robust upon excluding these target industries. Finally, the shock of financial crisis might be unevenly distributed among firms and the bank should respond heterogeneously to firms with different shock exposure. Indeed, we find that the increase in collateral requirements are milder and the interest rate is also comparatively lower for SOEs. Being the most directly affected ones, foreign trading firms are charged with significantly higher interest rates as well as higher collateral requirements.

Aside from the rising collateral requirements, we are also interested in changes along other dimensions of loan policies. First, the "flight from maturity" grant banks a quick escape from worsening economic conditions. Consistent with this, we find that the average loan maturity shortened by 0.44 months while for unsecured loans, which are the most exposed to borrower credit risk, the magnitude of maturity shortening jumps up to 0.434 years. The maturity shortening indicates stricter financing constraints for firms, which may make them refrain from long term investments including R&D. Second, the banking literature has long documented the presence of relational lending (Hoshi et al. 1990a; Petersen and Rajan, 1994; Chodorow-Reich, 2014). We confirm that pre-existing relationship raises both the probability and the volume of funding. However, the power of relationship weakens substantially in the credit boom during the GFC. As "soft collateral", relationship seems to be replaced by solid collateral.

The change in bank loan policy may induce firms to alter their behaviors. As argued by Campello and Hackbarth (2012), firms' investment spending is affected by the availability of financing and additional investment in tangible assets relaxes borrowing constraints. With banks further raising collateral requirements, firms may change their investment decisions accordingly to facilitate future funding needs. Investing in real estates could help firm obtain funding from banks while the products of intangible investment are usually not accepted as collateral. Thus, it is likely that the rising collateral requirements may induce firms to prioritize real estate investments over intangible investments such as R&D. Merging the loan records with China's Annual Survey of Industrial Enterprises and enterprises' patent application data, we find that firms with increased share of asset-based loans also apply for significantly less patents and this is especially prominent for firms with rising mortgage loan share. This indicates the possible real impacts associated with bank's changing collateral requirements and provide some evidence for recent salient macroeconomic facts on China including the slowing economic growth, declining TFP growth rate, and the subsequent housing boom.

The paper is related to four strands of literature. First, recently there are increasing research on corporate debt structure and borrowing constraints. We provide stylized facts from emerging markets which complement the current literature and thus facilitate cross country comparison. Macro finance literature usually links firm's borrowing capacity with cash flows from firms' operations or the liquidation value of physical assets that could be used as collateral (Stiglitz and Weiss, 1981; Holmstrom and Tirole, 1997; Hart and Moore, 1994; Hart and Moore, 1998; Kiyotaki and Moore, 1997; Bernanke et al., 1999; Mendoza, 2010). Lian and Ma (2021) distinguish between asset based debt and cash flow based debt, and document the prevalence of the latter among U.S. nonfinancial firms. Using a comprehensive bank loan dataset with details on underlying collateral, Caglio et al. (2021) highlight the heterogeneity in borrowing constraints for different firms and shows that collateral requirements are higher for small and medium enterprises. Using a unique bank loan level dataset, we provide stylized facts on the Chinese bank loan collateral composition and find that the patterns in China share some commonalities with but also differ from the U.S. in many dimensions.

Second, this paper contributes to the large body of literature on the bank lending channel of monetary policy transmission but emphasizes the importance to distinguish between loan types (Bernanke and Gertler, 1995; Chodorow-Reich, 2014; Jiménez et al., 2020). Previous literature explores how bank credit supply is influenced by either monetary policy or financial shocks but remains mostly silent on the impact of the two factors combined, i.e., the problem of credit allocation in credit expansion during a financial crisis (Kashyap et al., 1993; Kashyap and Stein, 2000; Ivashina and Scharfstein, 2010). The prominent features of crisis include drastically worsening economic environment and heightened uncertainty. Even with cheap and abundant funding, to whom and in which form should the banks allocate the money remains an intriguing question. Focusing on the credit boom during the GFC, we explores the possible answer to this question from the perspective of collateral structure.

The heterogeneity in collateral constraints could lead to different implications for credit allocation and may affect monetary policy transmission through the bank lending channel (Lorenzoni, 2008; Diamond et al., 2020; Crouzet and Eberly, 2018). Indeed, Caglio et al. (2021) find that monetary policy transmission and risk taking differ across different types of firms and their findings imply that the firm size distribution and collateral type matter for the aggregate effect of monetary policy. Ivashina et al. (2021) emphasize the importance to distinguish between loan types while investigating the effects of monetary policy or financial crisis. They show that cash-flow loans are the main drivers and asset-based credit is mostly insensitive. Nevertheless, it remains elusive on how credit supply across loan types would change when credit boom occur contemporaneously with crisis. Different from their findings, we show that the combination of easing monetary policy and financial crisis points to the expansion of asset based loans dominating that of cash flow based loans.

By directly examining the question of how credit gets created and allocated during the credit boom, our paper contributes to the literature on credit allocation in China during the financial crisis. Rather than focusing on credit reallocation across sectors differentiated by ownership, we provide a new perspective by examining the changing collateral requirements of banks. The most related paper is Cong et al. (2019) and they study the credit allocation across firms and its real effects during China's economic stimulus plan of 2009 - 2010. They find that the credit expansion disproportionately favors state-owned firms and firms with lower production efficiency. Focusing on the credit allocation between the public and private sectors, Huang et al. (2020) show that the massive post-crisis increase in local public debt crowded out private investment. This finding resonates with the decrease in production efficiency and economic growth as private firms have much higher productivity than SOEs (Song et al., 2011). Our paper investigates the credit allocation problem from the perspective of loan type and points out that aside from credit reallocation across different types of firms, there is also a reallocation across different loan types. The rising collateral requirements could help explain the credit reallocation towards firms with lower efficiency and may further contribute to the declining economic growth rate over time.

Finally, our paper is related to the literature that focuses on finance and misallocation and offers related empirical evidence. Rather than placing finance as a side show, the finance and misallocation literature points out that financial constraints could have real impacts (Buera et al., 2011; Moll, 2014). Midrigan and Xu (2014) further evaluate the role of financial frictions in determining total factor productivity. Concerning collateral and misallocation, current theoretical works emphasize the impact of collateral constraint over the business cycle (Gorton and Ordonez, 2014; Asriyan et al., 2021). Our paper contributes to this strand of literature by showing empirical evidence of increased collateral requirements in bank loans accompanied by reduced firm innovation.

The paper proceeds as follows. The next section first introduces the background on the credit boom in China during the GFC. We then perform a detailed description on our dataset and provide some stylized facts about the bank loan collateral structure and its determinants. With a thorough understanding of our data and the basic loan structure, we then present our empirical strategy and baseline findings in section 3. Section 4 provides robustness checks and heterogeneity analysis while section 5 discusses other dimensions on bank loan policy. Upon knowing how bank loan collateral structure changes post the GFC, we further investigates the possible real impacts in section 6. Section 7 concludes.

2 Background, Data, and Stylized Facts

2.1 China's 2008 Economic Stimulus Plan

With heavy reliance on international trade, the Chinese economy experienced a substantial hit during the 2007-2009 GFC. China's GDP growth rate fell to 6.8% in the fourth quarter of 2008 from 9% in 2008Q3, only about half of the 13% yearly growth rate in 2007. In response to the drastic shock, Chinese government rolled out a massive economic stimulus package which is a combination of fiscal and credit programs in November 2008. Cong et al. (2019) provide a detailed introduction on the structure of China economic stimulus plan.

The fiscal part of the stimulus plan, which is also widely recognized as the "four trillion stimulus package", entails government spending 4 trillion RMB on a wide range of infrastructure and social welfare projects, including 1 trillion on infrastructure repairs following the 2008 Wenchuan earthquake. Among the 4 trillion, the central government funded for about one third and the remaining were expected to be funded by local governments. Bai et al. (2016) show that the local government part of the stimulus was largely financed by local financing vehicles that borrowed and spent on behalf of local governments and the funding mainly originates from bank credit (Chen et al., 2020).

Aside from boosting government spending, the Chinese government also encouraged substantial bank credit expansion by simultaneously raising lending quotas, lowering required reserve ratio, and decreasing the benchmark lending rate. Panel A in Figure 1 presents the monthly changes in the outstanding amount of bank loans from the total social financial data of the People's Bank of China. Consistent with the credit boom, there is an unprecedented surge in the bank loan volume starting from 2008Q4. We then investigate the question of how the bank credit gets created and allocated during the crisis.

2.2 Sample Description

We obtain proprietary data on bank loan contracts issued by one of the big four state-owned commercial banks in a big city located in east China provinces from March 2006 to June 2010. As we mentioned earlier, most of the credit were distributed out through banks during the 2008 Chinese economic stimulus, among which state-owned commercial banks constitute the major force. Being one of the big four state-owned banks, our issuer alone covers about 8% of total bank loans outstanding in that prefecture city in 2006 - 2007 and the number doubles to 16.9% by the end of 2008 (See Figure A1 in Appendix). As shown in panel B of Figure 1, the total outstanding bank loan volume also rises sharply starting from the fourth quarter of 2008, consistent with the aggregate bank loan pattern as shown in panel A. The surge in market share and loan volume is in line with the fact that state-owned banks play a major role in the 2008 credit boom. Nation-wide speaking, our issuer accounts for around 10% of total outstanding bank loans, close to the number from our sample. This shows that the banking market structure of this city is similar to the country average, alleviating the concern that this city might be an outlier compared to the rest of the country. Focusing on a representative state-owned commercial bank covering both pre- and post- 2008 periods, our sample is appropriate for exploring how credits get created and allocated when banks face the tension of high economic uncertainty and mandatory credit expansion during the GFC.

[Insert Figure 1 Here]

Our data provides comprehensive and detailed information about the underlying bank loans. For the lender side, the name and ID of the issuing branch for each loan are recorded. Concerning the borrower side, we know the firm name, firm ID, industry, bank internal rating, firm size, and firm ownership. [2] [3] For each loan, the data includes loan-specific ID, interest rate, total volume, start date, maturity, classification of the loan (pass, special mention, substandard, doubtful, loss), special mention (substandard, doubtful, or loss) value, loan officer, loan type, and details on the underlying collateral or guarantors, if applicable.

There are three features that make our data especially interesting. First, due to data constraint, previous researches on the 2008 China's credit boom mostly rely on the Chinese Annual Survey of Industrial Enterprises (ASIE) which covers manufacturing firms only. Our

[2]The industries recorded in the data are not aligned with the Chinese industrial classification for national economic activities. For example, in our sample, trading firms are classified according to the type of trading partners, and are thus grouped as domestic trading and foreign trading firms. However, the industrial classification for national economic activities classifies firms according to the commodities traded.

[3]Rating and firm size also follow the bank's internal guidelines. Bank's internal guidelines usually follow related regulations and law. For the classification of firm size, the bank follows the guidelines of National bureau of statistics in China and combines four dimensions of information: employment, sales revenue, total asset, and industry.

data, however, includes bank loans to over 23 industries spanning from manufacturing industries such as textile to service industries like tourism. [4] As shown in Figure 2, manufacturing industries only account for around 60% of total loan volume. Service industry accounts for 15% and another 20% goes to transportation, construction, and utility industries. Note that the value share of loans to manufacturing firms drops while that for transportation, construction, and utility rises post 2008q4. This might be an outcome of the four trillion stimulus plan which emphasizes investment in target industries like transportation and construction.

[Insert Figure 2 Here]

Second, our bank loan data includes a large number of loans to small and medium firms (SMEs). Loans for small firms are also missing in the previous research using bank loan data collected by the Chinese Banking Regulatory Commission as it only covers firms with annual outstanding balances equal or above 50 million RMB (Cong et al., 2019). As for other commonly used datasets, listed firms are mostly of large-size and ASIE data is effectively a census on medium and large firms. [5] Our data thus provides an interesting opportunity to take a glance at the part of firms that are usually missing in other datasets. Finally, our bank loan data also specifies details on the *underlying collateral* which enables us to explore how collateral constraint changes during the 2008 credit boom.

Before further analysis, we perform the following data cleaning procedure: (i) drop observations with missing firm ownership; (ii) keep loans denominated in RMB only; (iii) drop loans with missing or abnormal loan volume; [6] (iv) drop loans with 0 interest rate or 0 maturity, as these are likely to be wrongly recorded. The final sample includes 31,797 loans issued to 2,828 firms. Among all firms, 1,351 (47.77%) are small firms and 1,223 (43.25%) are of medium size. In terms of ownership, only 139 firms are state-owned and the rest 2,689 all belong to private enterprises.

[4] The industries include: light industries, machining, textile, domestic trade, real estate, municipal infrastructure, electronics, transportation, electricity, foreign trade, chemical, pharmaceuticals, petrochemical, metallurgy, transportation, construction, construction material, agriculture, finance, tourism, military, tobacco, communication service, coal, etc.

[5] The threshold for annual sales is 5 million RMB until 2010 and rises to 20 million RMB from 2011 onward.

[6] Here "abnormal volume" includes the following circumstances: (1) loans recorded as normal but with positive special mention, substandard, doubtful, or loss volume; (2) loans classified as special mention (substandard, doubtful, or loss) but with 0 special mention (substandard, doubtful, or loss) volume;

2.3 Summary Statistics

Panel A in Table 1 presents the summary statistics on loan volume, interest rate, and maturity for the whole sample. There is vast heterogeneity in terms of loan size with the standard deviation being 16.2 million RMB. The average loan volume is 5.13 million RMB, which far outsizes the median of 1.5 million RMB. This indicates that there is a large number of small loans and a few with enormous size. Panel A also shows the summary statistics on the value of loans classified as special mention, substandard, doubtful, or loss. The last three types of loans are considered as nonperforming. The first thing worth noting is that these circumstances are quite rare with over 95% of the loans being recorded as pass. There are some loans marked as special mention but nonperforming loans are extremely rare. In fact, the 99^{th} percentiles for substandard, doubtful, and loss value are still 0. The low nonperforming loan ratio may be evidence for the strong balance sheet of the state-owned banks.

In terms of interest rate, the simple (volume weighted) average interest rate is 5.66% (5.77%). These numbers stay close to the benchmark lending rate assigned by the central bank of China. The last row in panel A shows the summary statistics on loan maturity. The simple average of loan maturity is 0.71 years. As a comparison, the volume weighted average loan maturity is 1.61 years, meaning that larger loans also tend to have longer maturity. Interestingly, half of the loans in our sample have a maturity of less than 6 months and 95% is within one year. The overwhelming majority of short-term bank loans is more of a country-wide phenomenon than due to sample selection bias. Another dataset containing loans originated by the nineteen largest Chinese banks covering around 80% of total outstanding bank loans to Chinese firms also exhibits a similar pattern, with more than 75% of loans being short-term (Cong et al., 2019).

[Insert Table 1 Here]

To provide a more detailed examination on our bank loan data, panel B in Table 1 further classifies bank loans according to firm's ownership structure, size, and rating. First of all, in terms of ownership structure, **SOE loans are of larger size, lower rate, and longer maturity**. The majority of loans in our sample flow to non-SOE firms. Non-SOE firms account for 83.45% of total loan volume and 93.17% of total numbers of loans. As we mentioned earlier, only 139 firms in our sample belong to SOEs. The relatively smaller share of SOEs could be explained by the fact that the city is located in east China with very active private sector. State-owned firms are relatively less powerful there. [7] Panel (a) and (b) in Figure 3 present the value-weighted interest rate and maturity distribution for SOEs and Non-SOEs, respectively. The gray lines are for SOEs and the navy lines are for Non-SOEs. In terms of interest rate, panel (a) indicates that prior to 2008q4, SOEs and Non-SOEs do not significantly differ in terms of borrowing cost. There are even certain periods when SOEs would be assigned a higher cost on average as compared to Non-SOEs. Post 2008q4, however, there emerges an obvious gap between the borrowing costs of Non-SOEs and SOEs, with SOEs sharing a lower rate. Besides, the overall pattern in panel (a) shows that interest rate experiences a sharp decline starting from 2008q4, dropping from around 7% to about 5%. This is because as part of the stimulus plan, the central bank of China lowered its benchmark lending rate, which constitute the lower bound of bank's lending rate. The benchmark lending rate for loans with maturity between 6 months and 1 year was lowered by 2% in 2008q4, from 7.47% to 5.31%. The pattern in panel (a) perfectly squares with the policy change. Panel (b) shows the volume share of short-term loans for these two types of firms.[8] SOEs always have a smaller share of short-term loans, indicating that SOE loans are of longer term. The fact that Non-SOEs borrow short term means that these firms are imposed with a higher degree of financial constraints.

[Insert Figure 3 Here]

We also classify bank loans according to firm size. **As firm size goes up, loans are larger with lower average rate and longer maturity**. In our sample, over half of the loans flow to medium-sized firms. Loans to large firms account for 37.95% of total loan volume but only 13.26% in terms of the number of loans. This indicates that loans to large firms are also of far larger size. The most interesting part of our data is that it also covers a considerable amount of loans for small firms. This part of loans only take up 11.49% of total loan volume but account for 36.09% in terms of loan contracts. As private

[7] Note that we can not exclude the probability that some firms might be registered as private firms but are in reality controlled by state-owned firms or institutions if we trace further back to its ultimate holder. It is also likely that some state-owned firms might be acquired and controlled by private firms and yet still recorded as SOEs in our sample. Both scenarios are likely to occur. As we would not emphasize the ownership structure in this paper, this would not pose severe problem for our analysis.

[8] Here short term means loans with maturity less or equal to one year.

small and medium enterprises constitute a non-negligible driving force for Chinese economic growth prior to 2008 and they also shoulder the majority of employment and investment, it is important to understand how bank credit access alters for these firms during the credit boom in 2008. Panel (c) and (d) in Figure 3 present the average rate and maturity distributions for firms of different size. The navy, light blue, and dashed gray lines are for small, medium, and large firms, respectively. As shown in panel (c), the navy line almost always lies above the other two and the dashed gray line is usually the lowest of the three. This means that borrowing cost drops as firm size goes up and small firms are charged with the highest rate. The positions of the three lines are the same in panel (d). Aside from having the highest rate, loans to small firms are also more likely to be short-term. The higher borrowing cost and shorter maturity both reveal the less favorable borrowing conditions for the small firms.

Finally, in the bottom part of panel B in Table 1, we report the summary statistics of bank loans according to firm rating. Ratings are grouped into four bins: AAA-A, BBB-B, CCC-D, no rating. [9] As Chinese state-owned banks are usually rather stringent in risk management, it is not surprising that the majority of loans are issued to AAA-A and BBB-B firms. Loans for AAA-A firms are usually of larger size, compared to those for BBB-B firms. Interestingly, loans for CCC-D firms are much larger with the average loan size being 1026.7 million RMB, exceeding that for AAA-A (701.96 million) and BBB-B firms (487.03 million). The larger size is possibly related to the specific industries of the lower rating firms. Panel (e) in Figure 3 shows the value-weighted average interest rate for firms in these four rating bins. Except for loans to firms with no rating, the rest three lines are consistent with usual understanding that riskier firms have higher borrowing cost. The maturity distributions in panel (f) are quite messy and do not show any particular pattern. Nevertheless, one thing is consistent with the previous panel (b) and (d): there is overall an upward trend over time, meaning that there might be a maturity shortening. For firms with no rating, the average loan size is the smallest, with its average maturity being the shortest and interest rate being the lowest. We will see later that firms with no ratings mainly borrow through pledging banker's acceptance, commercial acceptance, or certificates of deposit. These securities are short-term and are more liquid than collateral such as real estate. The high quality and short maturity of the pledged collateral could explain for the characteristics of the bank loans for

[9] The issuer bank would not assign ratings to government-affiliated institutions. Also, for borrowers with no borrowing history, the current rating would also be empty.

no-rating firms.

2.4 Overview of Collateral Composition

One remarkable feature of our bank loan data is that it specifies the type of bank loans. That is, it specifies whether a bank loan is unsecured, guaranteed, mortgage, or pledge loan. For guaranteed, mortgage, and pledge loans, the data also specifies the type of guarantors, or the type of collateral. These four types of loans differ in terms of the underlying collateral. Unsecured loans and guaranteed loans are backed by credit, only that unsecured loans rely on the borrower's credit alone while guaranteed loans are based on the credit of both the borrower and the guarantor. Mortgage and pledge loans, on the other hand, are backed by assets. Recent literature distinguishes between asset based loans (ABLs) and earning-based loans (EBLs), or going-on concern debt (Lian and Ma, 2021; Kermani and Ma, 2021). ABLs are loans secured by fixed assets, real estate, cash and marketable securities, and account recievables and inventory (AR&I). The value of ABLs are determined by the liquidation value of the collateralized assets. In contrast, the value of EBLs derives from firm cash-flows. Under this criterion, mortgage and pledge loans are ABLs while unsecured and guaranteed loans fall under EBLs. As our data also includes details on the underlying collateral type, we could provide a more granular grouping of the loans while keeping a consistent mapping with the existing literature.

In this subsection, we will first provide baseline stylized facts on the collateral composition of bank loans. Loan level data with detailed information on the underlying guarantees or collateral is hard to obtain. As far as we know, there are two papers that study the underlying collateral structure of bank loan: Caglio et al. (2021) with U.S. administrative firm-bank-loan level data covering over 85% of U.S. banking sector since 2012, and Ivashina et al. (2021) with detailed credit registry data from Peru and Spain. This section complements the existing research by providing stylized facts on bank loan collateral composition. The collateral composition in China bear some commonalities with U.S. and Spain, but there also exists vast differences. These stylized facts would facilitate cross-country comparison and deeper understanding of this topic.

2.4.1 Earnings-based Loans (EBLs)

Figure 4 shows the composition of the four types of loans in our sample. Unsecured loans account for 17.35% of total loan volume and 3.47% of total numbers of loans. With no protection provided by guarantees or collateral, unsecured loans are completely backed by the borrowers' creditworthiness. Thus, only those large firms with strong credit would be able to obtain unsecured financing. Figure 5 presents the maturity distribution for different types of loans. The maturity of unsecured loans tends to be longer as compared to other types of loans, with 35% of loans being one year or longer term loans.

[Insert Figure 4 Here]

Aside from borrower's own creditworthiness, guaranteed loans require further credit enhancing through guarantees provided by third-parties (the guarantors). As specified by the Civil Code of the People's Republic of China, the forms of guarantee include general guarantee and joint and several liability guarantee. In the case of general guarantee, the guarantor shall bear guarantee liability when the debtor fails to perform his obligation. In the case of joint and several liability guarantee, the guarantor and the debtor are jointly and severally liable for the obligation. The major difference is that the creditor is better protected in the case of joint and several liability guarantee as the guarantor would assume stronger liability. Chinese banks are usually the more powerful side and would usually require the guarantor to assume joint and several liability. So, guaranteed loans are based on the creditworthiness of the borrower and the guarantor combined. 20.29% of loans in our sample are guaranteed loan, together taking up 33.89% of loan volume. Among all guaranteed loans in our sample, 28.4% has a maturity of 3 - 6 months and there is another 47.75% with a maturity between 6 months - 1 year. The majority of guaranteed loans are short-term, consistent with the overall pattern. Panel A in Table 2 decomposes the guaranteed loans based on guarantor types. Among the 6,453 guaranteed loans, 5,265 (81.59%) are guaranteed by other firms. Forming cross guarantees and guarantee networks is a common approach for obtaining credit among private economies. There are also some loans that rely on large state-owned firms, commercial banks, or policy banks as guarantors, but the number is quite limited.

[Insert Figure 5 Here]

Unsecured loan and guaranteed loan should both be considered as EBLs as their valuations both rely on firm's cash flows. Taken together, 51.12% (23.76%) of the loans are EBLs in our sample in terms of value (numbers of loans), similar to the case in Spain. Note that though guaranteed loans constitute a considerable part of our loan sample and account for about 1/3 of total loan volume, this type of loan is not seen in U.S. (Caglio et al. (2021)). There is also one type of EBLs that is important in U.S. but not seen in our sample, the blanket liens. Blanket liens are loans secured by substantially all assets of the firm aside from the asset already used as collateral. In the U.S. data, blanket liens account for about 30% of total loan value for all firms except for the largest public ones. To our understanding, the reason that blanket lien is not seen in China is because of legal issues. Under the current relevant guarantee system of the Civil Code of the People's Republic of China, it is required that the movable under lien should be in the same legal relationship as the debt claim. [10] The legal requirements restricts the lien in China to possessory lien applicable to movables only. Thus, blanket liens popular in U.S. that put all firm assets under lien to back future debt repayment are not compatible with China's legal system.

[Insert Table 2 Here]

2.4.2 Asset-based Loans (ABLs)

Among all four types of loans, mortgage loans are the largest both in terms of volume and loan number. 47.89% of loans in our sample are mortgage loans, accounting for 39.09% of total loan volume. The relatively smaller share in terms of loan volume indicates that individual mortgage loan size is on average smaller than the sample average. This is contrary to the case in Spain and Peru, where asset based loans far outsize cash flow based loans. As can be seen from figure 5, the maturity distribution of mortgage loans is quite close to that of guaranteed loans. But different from unsecured and guaranteed loans which are both credit-based, mortgage loans are backed by physical assets, especially real estates. Panel B in Table 2 provides further details on the types of underlying collateral used in mortgage

[10] Article 62 of the Interpretation of the Supreme People's Court of the Application of the Relevant Guarantee System of the Civil Code of the People's Republic of China: Where a debtor fails to perform its debts when they become due, and the creditor has a lien in and lawful possession of the movable of a third party by reason of the same legal relationship, and claims priority of payment from the property under lien, the people's court shall uphold the claim. The previous version of property law imposes a similar requirement, though the wording is slightly different.

loans. Real estate for manufacturing purposes, such as factory buildings and land, are the most common type of collateral. As shown in panel B, 88.88% of mortgage loans are backed by these assets. In some cases, though uncommon, banks also accept residential real estate (2.13%) and chattel (1.23%) as mortgage collateral.

There is one last type of loan that is also collateral based, the pledge loan. One important feature that distinguishes pledge loans from mortgage loans is that the possessory title to the pledged property owned by the pledgor would be conveyed to the pledgee in a pledge loan. In the case of mortgage loans, the borrower could still continue using the collateral while the loan contract lasts but not so in the case of pledge loan. The possessory title transfer limits the range of assets used in pledge loans. Unlike mortgage loans where collateral typically includes physical assets (hard to deliver or transfer), pledge loans usually use financial assets (easy to deliver). The pledged assets in our sample are mostly banker's acceptance bills, commercial acceptance bills, certificates of deposit, or other financial assets. Compared to physical assets such as real estate, the financial assets used in pledge loans are usually more liquid and with market prices. With the high quality and liquidity of the collateral, in addition to the actual delivery of the pledged asset, pledge loans should be the safest type of loans and the least reliant on borrower's credit.

In our sample, 28.35% of bank loans are pledge loans but taken together, they only account for 9.79% of loan value. Panel C of Table 2 shows the composition of different types of collateral in pledge loan. Among all 9,015 pledge loans, 5,978 (66.31%) are backed by banker's acceptance and only 358 are backed by commercial acceptance. Banker's acceptance is a promised future payment from a bank while in the case of commercial acceptance bill, the payment is promised by a non-bank institution. In the early 2000s, banks in China bear implicit government guarantee and it is believed that banks would never default. Thus, banker's acceptances bills are safer assets compared to commercial acceptance bills. With the majority of collateral being banker's acceptance bills, pledge loans should be very safe. Note that the maximum maturity of banker's acceptance bill is 6 months, which then limits the maturity of pledge loans. [11] Indeed, Figure 5 shows that the majority of pledge loans locate in the maturity bucket of 3 - 6 months. Aside from acceptance bills, RMB certificates

[11] It is required that banker's and commercial acceptance bills should all be gradually shifted from paper version to electronic version post 2009. The longest maturity of electronic acceptance bill is extended to 1 year.

of deposits are also used in pledge loans. Other types of collateral include foreign currency denominated certificates of deposit, foreign exchange, sovereign bonds, financial bonds, etc.

Both mortgage and pledge loans are ABLs and they account for 48.88% of loan value in our sample. It is interesting to make a comparison between the types of the collateralized assets in our sample and in the U.S. In our sample, the two mostly widely used types of collateral are real estate and banker's acceptance bill. Banker's acceptance bills would be classified as marketable securities but all cash and marketable securities only make up a tiny portion of total U.S. firm loans. In the U.S. data, collateral for ABLs includes the following assets: real estate, fixed assets, cash and marketable securities, and accounts receivable and inventory (AR&I). Among U.S. private firms, loans that use fixed assets and AR&I as collateral account for 30% - 50% of total firm loans, among which AR&I takes up a larger share. These two types of collateral, however, are absent or rarely-used in our bank loan data.

2.5 Collateral Composition and Firm Characteristics

In the previous subsection, we present an overview of collateral composition in our sample. The four types of bank loans differ in the requirements for guarantees and collateral. This naturally leads to some further questions: what kinds of firms could obtain unsecured, guaranteed, mortgage, or pledge loans? For firms borrowing through the same type of bank loans, do they share any common characteristics that lead to the credit allocation outcome? In this subsection, we link bank loan type with firm characteristics and investigate the determinants of collateral composition.

2.5.1 SOEs Face Lower Collateral Requirements

The first dimension that we consider is ownership. This is especially relevant in China as the ownership structure means far more than simply its equity holding structure. As we already see in section 3.2, SOE firms are often privileged in obtaining credit compared to Non-SOEs. This is on the one hand consistent with political targets such as supporting state-owned sectors. On the other hand, SOEs are inherently backed by governments and they are unlikely to default. Banks thus have both political and economic incentives to channel funding to SOEs. What's more, as SOEs bear higher creditworthiness, banks should not emphasize too much on additional credit enhancement such as guarantees or collateral. Figure 6 shows that this is indeed the case. We report the volume shares of the four types of bank loans for SOEs and Non-SOEs separately. About 40% of loans are unsecured for SOEs while the number is only 12.6% for Non-SOEs. SOEs tend to use fewer guaranteed and mortgage loans, as compared to Non-SOEs. Interestingly, SOEs also have a larger share of pledge loans, though the difference is relatively modest. Availability of banker's acceptance bills might limit the possibility of applying for pledge loans for Non-SOE firms. [12] Overall, SOEs have a lower ratio of ABLs and face lower collateral requirements.

[Insert Figure 6 Here]

2.5.2 Lower Collateral Requirements for Larger Firms

There also exist vast differences in the collateral compositions for firms of different size. As shown in Figure 7, one third of the total value of loans for large firms is unsecured and another 1/3 is guaranteed. Among the rest 1/3, 2/3 is backed by mortgage collateral and the rest goes to pledge loans. This means that the value of EBLs is twice the value of ABLs for large firms. For medium-sized firms, a stark difference is that the value ratio of unsecured loans shrinks to merely 8.29%. Compared to large firms, the share of guaranteed loans is about the same but that for mortgage loans more than doubles. Taken together, the ratio of EBLs and ABLs for the medium sized firms is about 1:1. The left bar in Figure 7 present the case for small firms. For these firms, the overwhelming majority of bank loans is mortgage loans, which account for 60.4% of total loan value. The second largest is guaranteed loans but its value share is only 25.25%. The ratio of EBLs and ABLs now falls to 3:7. As firm size goes up, the ratio of EBLs goes down, and the collateral requirement would be higher.

[Insert Figure 7 Here]

2.5.3 Lower Collateral Requirements for Higher Rating Firms

We also explore the collateral composition for firms in different rating buckets. Before digging into the data, a natural prediction would be that collateral requirements for higher

[12] There is usually a quota for the maximum amount of acceptance bills a bank could issue. Thus, banks face the problem of allocating the quota among its customers. It is likely that Non-SOEs might be disfavored in this process.

rating firms would be lower. Collateral is posed to protect lenders in case borrower defaults. Higher rating firms would be less likely to default, thus collateral is less relevant for loans to these firms. The pattern in Figure 8 is roughly consistent with this prediction. For firms with the highest ratings (AAA-A), 27.2% of loans are unsecured and 34.94% loans are guaranteed, indicating that over 60% of the loans are purely credit based. For the BBB-B firms, however, the ratio of unsecured loans shrinks to 14.07% and that for mortgage loans expands from 28.94% to 44.49%. The total share of EBLs drops to 48.66%, indicating a shift to more asset based borrowing. The collateral composition for CCC-D firms are very close to that for BBB-B firms. The collateral composition for firms with no ratings is quite interesting. Over 90% of these loans are pledge loans. Note that firms with no ratings include firms with no previous borrowing history at the issuer bank. A possible explanation would be that, when lending to new clients, it might be safer to start from lending through pledge loan as this provides the safest collateral.

[Insert Figure 8 Here]

2.5.4 Regression Analysis on the Determinants of Collateral Composition

In the previous subsections, we analyze the collateral composition for firms of different ownership structure, size, and ratings. However, different dimensions of firm characteristics may overlap. For example, larger firms might be more likely to be rated high and SOEs are on average larger than Non-SOEs. Sorting on one dimension alone provides interesting facts but may not be so rigorous. Thus, in this subsection, we would use regression analysis to simultaneously control for different firm characteristics and see which dimension matters most in determining firm's collateral composition. We use the following regression model:

$$
\begin{aligned}
Loanshare_{k,i,t} = \alpha_0 + \alpha_1 SOE_{i,t} + \sum_{\{Rating=High,Medium\}} \alpha_{2,Rating} Rating_{i,t} \\
+ \sum_{\{Size=Large,Med\}} \alpha_{3,Size} Size_{i,t} + FEs + \epsilon
\end{aligned}
$$

Where k, i, t stands for loan type (unsecured, guaranteed, mortgage, or pledge), firm, and year-quarter, respectively. The dependent variable $Loanshare_{k,i,t}$ is the outstanding value of bank loan type k as a share of the total outstanding bank loan value for firm i by the end of quarter t. Thus the dependent variable represents firm's collateral composition. As for the independent variables, we include dummies for different firm characteristics. $SOE_{i,t}$ is a dummy variable that equals to 1 if firm i is a SOE in quarter t. Similarly, $High$ and $Medium$ equal to 1 if firm i falls in the rating bucket of AAA-A or BBB-B in quarter t, and 0 otherwise. We can define size variables $Large$ and Med accordingly. We include industry*Year-quarter fixed effects and cluster standard errors at firm level. Note that the dependent variable is constraint within the range of $[0, 1]$. To address this concern, we try replacing the dependent variable with dummy variables that equal to 1 if the value share is positive, and 0 otherwise. We then run Logit analysis instead and all other settings remain the same.

Table 3 presents the regression results. The OLS analysis for value shares are in odd columns and the logit analysis are in even columns. Column (1) - (2), (3) - (4), (5) - (6), and (7) - (8) are for unsecured, guaranteed, mortgage, and pledge loans, respectively. First, for unsecured loans, the results in column (1) - (2) consistently show that SOEs with large or medium size and of the highest ratings are more likely to obtain unsecured loans. As unsecured loans are backed by borrower's credit only, the borrower must be of high quality in multiple dimensions in order to be qualified for unsecured lending and this explains our findings here.

[Insert Table 3 Here]

The regression results on guaranteed loans are in column (3) - (4). It is interesting to see that the most important firm characteristic that motivates guaranteed borrowing is firm size. Taken together, it is the large or medium sized firm with low ratings that would borrow through guaranteed loans. Firm ownership does not matter. As guaranteed borrowing requires the credit of both the borrower and the guarantor, highly-rated firms would use unsecured loans instead and only firms with lower ratings could use guarantee as credit enhancement. Nevertheless, the credit enhancement effect of guarantees would be rather limited for small firms. As there remains some risk that the guarantee may be ineffective, banks would still prefer bigger firms as they are generally safer.

Column (3) - (4) present the results for the determinants of mortgage borrowing. SOEs have a significantly lower share (probability) of mortgage borrowing while ratings do not seem to have any statistically significant impacts. It is the small non-SOE firms, regardless of their ratings, that borrow through mortgage loans. Mortgage loans specify the asset used as collateral. This would be especially important when lending to small firms as these firms typically do not have much assets in total. The liquidation value of these firms would be limited and future cash flows could be rather volatile. Thus banks would require the specification of collateralized asset to ensure safety.

The last two columns in Table 3 show the regression analysis on the determinants of pledge loans. Overall, there is no obvious pattern and it is difficult to conclude that certain types of firms mainly borrow through pledge loans. From the perspective of the bank, with high quality short-term asset as collateral, pledge loans are the safest among four types of loans and are the most detached from the borrower per se. Thus, it is reasonable to see no obvious patterns among firms that use pledge loans.

To conclude: (i) highly-rated, large or medium sized SOEs borrow unsecured; (ii) lower-rated, large or medium sized firms, regardless of ownership structure, borrow through guaranteed loans; (iii) Small non-SOEs, regardless of ratings, use mortgage loans; (iv) firms that borrow through pledge loans exhibit no consistent pattern.

3 Empirical Strategy and Baseline Findings

This paper aims to investigate how bank responds to the political mandate of credit expansion under high economic uncertainty. An unconstrained bank would naturally reduce credit supply in an adverse economic environment. This option, however, is not available for Chinese banks during the GFC. The other option would then be to raise collateral requirement to secure repayment. Thus, we would like to see whether the collateral structure of bank loans changes post the GFC. In the following subsections, we introduce the empirical models and baseline findings.

3.1 Empirical Strategy

3.1.1 Volume Analysis

We first explore whether firm's collateral structure changes post the GFC through the lens of loan volume. The regression model we adopt is as follows:

$$Ln(1 + LoanVol_{i,k,q}) = \sum_{k=G,M,P} \alpha_{k1} Post_q * Loantype_k + \sum_{k=G,M,P} Controls * Loantype_k + Controls + FEs + \epsilon_{i,k,q} \tag{1}$$

where i, k, q stands for firm, loan type, and year-quarter, respectively. The data is at firm-loan type-quarter level. For each firm at the end of each quarter, as long as its outstanding loan volume is positive, there would be four observations corresponding to the four types of loans. The dependent variable is the outstanding loan volume of firm i in terms of loan type k by the end of quarter q (in log). A firm may not have exposure to all four types of loans simultaneously. For example, a firm i may have 10 million guaranteed loans and 15 million mortgage loans outstanding by the end of quarter q but it borrows 0 unsecured and pledge loans. In this case, we calculate $Ln(1 + LoanVol_{i,k,q})$ for guaranteed and mortgage loans using the actual loan volume but that for unsecured and pledge loans would be set to 0. For ease of presentation, G, M, and P is short for $Guaranteed$, $Mortgage$, and $Pledge$, respectively.

We adopt an empirical method that is close to Difference-in-Differences setting where the unsecured loans are the baseline group and 2008q4 is the cutoff in time. This empirical setting allows us to control for factors that affect all four types of loans simultaneously and better tease out the actual shift in loan structure. Thus, the estimated changes in loan volume here is the relative difference as compared to unsecured loans. Besides, constructing the data in this way allows us to control for firm*year-quarter fixed effects in the most strict setting. Firm*year-quarter fixed effects could absorb all time varying variables related to firms such as shifting credit demand (Khwaja and Mian, 2008). As we do not have firm balance sheet data, including firm * year-quarter fixed effects could help alleviate this concern.

The parameter of interest here is α_{k1}. $Post_q$ is a dummy that equals to 1 if quarter q is post or equal to 2008q4, and 0 otherwise. Similarly, $Loantype_k$ are dummies that indicate whether the observation is for loan type k, where k stands for either $Guaranteed$, $Mortgage$, or $Pledge$. α_{k1} is the parameter for the interaction term $Post_q * Loantype_k$ and it represents how the outstanding volume of loan type k changes post 2008q4 compared to unsecured loan.

In the previous section, we present the collateral composition and show that some firm characteristics are associated with the prevalence of certain types of bank loans. Thus, in order to tease out the effects of bank loan collateral policy change, we need to control for multiple dimensions of firm characteristics. In all regression models, we include firm rating fixed effects (FEs hereafter) interacted with loan type FEs, size FEs interacted with loan type FEs, and firm ownership FEs interacted with loan type FEs. [13] These FEs enable us to control for the possibility that firms of certain rating or size group, or of certain ownership structure, would be more likely to have larger volumes of certain types of loans. Also, each loan would specify the industry that the money would be used for (loan usage) and the loan-specific industry may not be consistent with the industry that the firm belongs to. [14] To control for the industry related factors, we compute the outstanding volume share of loans in each industry for each firm by the end of each quarter and include these industry share variables as extra controls. Similarly, We could define bank branch share variables to control for possible differences in bank branches. These share control variables are also interacted with loan type dummies to control for industry or bank related prevalence in certain types of loans.

3.1.2 Volume Share Analysis

Regression analysis on the loan volume allows us to investigate the volume changes of different types of loans compared to unsecured loan. However, the Difference-in-Differences setting means that we could only obtain relative changes between loan types but not the absolute change. Also, the volume analysis predicts the direction of collateral structure change but remains ambiguous about the magnitude. So, in this subsection, we shift the focus of our analysis from outstanding loan volume to the volume share of different types of loans. The regression model is as follows:

$$VolShare_{i,k,q} = \beta_k Post_q + Controls + FEs + \epsilon_{i,k,q} \tag{2}$$

Thus, for each type of bank loan, we would run the above regression. Again, i, k, and

[13] We exclude all observations with no ratings in all following regression analysis.

[14] To give an example, an outdoor apparel company may simultaneously produce outdoor clothing and other outdoor equipment. The loans it applied for producing clothing would then be classified as loans flowing to textile and clothing industry while loans for manufacturing other apparel would be grouped to other industries such as plastic articles.

q stands for firm, loan type, and year-quarter, respectively. The dependent variable is the outstanding volume of loan type k as a percentage of total outstanding loan volume for firm i by the end of quarter q. The parameter of interest here is β_k. As in model (1), $Post_q$ equals to 1 if quarter q is equal to or post 2008q4, and 0 otherwise. The parameter β_k thus shows how the volume share of type k changes post 2008q4. We also control for bank branch variables, industry share controls, rating FEs, size FEs, and firm FEs.

The estimated parameter β_k shows how the composition of each type of loan shifts post 2008q4. Different from the parameter α_{k1} in model (1), β_K is no longer a Difference-in-Differences estimator and it directly measures the percentage change of different types of loans. Nevertheless, it also has some drawbacks as compared to model (1). As each regression is run at firm-quarter level, we would not be able to include firm * year-quarter fixed effects to absorb time varying firm-related variables that may alter its bank loan structure. For this reason, we keep both volume and volume share analysis and use them as complements.

3.2 Baseline Findings

Table 4 presents the regression analysis on loan volume (model (1)). Column (1) does not include any other fixed effects aside from the firm characteristics interacted with loan type fixed effects. The estimated coefficient for $Post$ controls for the average change in bank credit post 2008q4 and it is positive and significant at 10% level. This is consistent with the fact that there is a credit boom post 2008q4. The estimated coefficient for $Mortgage * Post$ is positive and significant at 1% level, indicating that compared to unsecured loans, the outstanding volume of mortgage loans rises by 35.4% post 2008q4. Similarly, the estimated coefficient for $Pledge * Post$ shows that outstanding pledge loan volume rises by 11.5% as compared to unsecured loans post 2008q4. The outstanding volume of guaranteed loans does not seem to experience any significant change as compared to unsecured loans as the coefficient for $Guaranteed * Post$ is negative but insignificant.

[Insert Table 4 Here]

Based on the setting in column (1), column (2) further controls for year-quarter fixed effects. Including the time fixed effects does not result in much changes in the estimated coefficients and corresponding t-statistics. Column (3) controls for firm fixed effects instead.

Firm fixed effects could explain a considerable proportion of the variation in outstanding volume share for different types of loans, as the adjusted R^2 rises sharply from 0.393 to 0.882. Including firm fixed effects also lead to large changes in the estimated coefficients. The coefficient for $Mortgage * Post$ increase from 0.354 to 0.558, meaning that the outstanding volume of mortgage loans goes up by 55.8% compared to unsecured loans post 2008q4, after controlling for firm fixed effects. The coefficient for $Pledge * Post$ declines a bit but remains positively significant at 5% level.

Column (4) includes both firm and year-quarter fixed effects. As time fixed effects could not explain much of the variation in the dependent variables, the regression outcome in column (4) is quite close to that in column (3). The most strict setting is column (5) where we directly control for firm * year-quarter fixed effects to absorb any firm-level time varying variables. Comparing between column (4) and column(5), we can see that the adjusted R^2 increases a bit, indicating that the firm*time fixed effects could further explain part of the variation that is missing in the previous regressions. But the magnitude of improvement remains modest. The estimated coefficients and t statistics are also very close to those in column (4). Even after controlling for time-varying firm level variables, our baseline regression results remain robust. Panel A in Table A1 replicates Table 4 but instead double clusters the standard error at firm and year-quarter level. The major findings remain robust.

[Insert Table 5 Here]

The regression results for volume share analysis are in Table 5. In column (1) - (4), we present the changes in the volume share for unsecured, guaranteed, mortgage, and pledge loans, respectively. Bank branch share controls, industry share controls are included in all regressions and fixed effects include firm rating, size, and firm fixed effects.[15] The volume share analysis directly explores the changes in bank collateral structure. A drawback here is that we could not control for time fixed effects or firm*time fixed effects. The general message in Table 5 is consistent with the findings in Table 4. The fraction of unsecured loans among total outstanding bank loans drops significantly by 0.7% post 2008q4 while that for guaranteed loans decreases by 2.8%. The volume share of outstanding mortgage

[15]Firm ownership fixed effects are omitted here as they are mostly absorbed by firm fixed effects. There is little time-series variation in firm ownership. We include firm-ownership fixed effects in Table 4 as they are interacted with loan type FEs.

loans, on the other hand, increases by 3.8%. As for pledge loans, the estimated coefficient remains positive but is insignificant. As Table 4 presents difference-in-difference analysis relative to unsecured loans and given that unsecured loans drop post 2008q4, it is likely that pledge loans experience no significant change and it is the reduction in unsecured loans that generates the positive coefficients for $Pledge * Post$ in Table 4. Similarly, panel B in Table A1 replicates Table 5 but double clusters the standard error at firm and year-quarter level and results remain robust.

To conclude, the main findings in Table 4 and Table 5 are consistent. Whether in terms of volume or volume share, the collateral structure of banks loans shifted from earnings-based loans (unsecured and guaranteed loans) to asset-based loans (especially so for mortgage loans) post 2008q4.

4 Robustness Checks and Heterogeneity Analysis

In the previous section, we present the baseline results on the change in collateral structure post 2008q4. The shift from earnings-based loans to asset-based loans is consistent with the idea that banks may raise collateral requirements while facing the tension between high economic uncertainty and political mandate of credit expansion. In this section, we further discuss some related issues and also try to rule out some possible confounding factors.

4.1 Credit Supply or Demand?

A concern on bank loans is whether the findings are driven by bank's credit supply or firm's credit demand. What we see in the data is the final outcome of bank loan issuance which depends both on credit supply and demand. Although our results are consistent with the collateral policy change from the supply (bank) side, here we will discuss the impact of possible demand side factors on our findings.

China's economy experienced a substantial shock during the 2007-2009 GFC given its high reliance on export back then. The supply side response is the rapid expansion of bank credit driven by government policy mandates. As for credit demand, the financial crisis weakens world-wide demand and some Chinese firms may struggle to survive given the loss of customers and demand shrinkage. This may affect firm's credit demand in two different ways. On the one hand, given the high economic uncertainty and large magnitude of shock, firms may curtail production and refrain from making investments. These lead to reduced credit demand. On the other hand, worsening economic environment may push firms under urgent need of money to sustain daily operation, which indicates rising credit demand. The ultimate change in credit demand depends on the relative strength of these two counteracting forces.

Regardless of the direction of credit demand change, we try to control for the possible influence of credit demand in three ways in the baseline analysis. First, in the volume analysis, we use a difference-in-difference setting where we estimate the volume changes of guaranteed, mortgage, and pledge loans compared to the volume of unsecured loans. The average change in credit demand would be differenced out. Second, in the most rigorous setting in Table 4, we directly control for firm*time fixed effects that could absorb any time-varying firm level factors including changing credit demands (Keil and Muller, 2020; Alfaro et al., 2021). Finally, Table 5 presents the volume share analysis where we compute the outstanding volume of each type of bank loan as a percentage of total outstanding bank loan of each firm at each quarter. The scaling irons out any fluctuations in total bank loan volume that might originate from varying credit demands.

Whether the credit demand rises or falls, its impact on our findings remains limited as long as it is associated with aggregate volume change but does not predict shift in underlying collateral structure. The implicit assumption in the above strategies is that firm's credit demand is the same across all types of bank loans given the same bank. Nevertheless, even if firm credit demand is indeed associated with structural changes in bank loan type, it seems to predict the opposite outcome. If it is at the will of firms when determining loan type, it is hard to imagine that firms would ever prefer to borrow under more restricted collateral constraint with no apparent interest rate improvements. Thus, the issue of credit demand is less a concern in our setting.

4.2 Varying Firm Composition?

The previous subsection analyses the possible influence of credit demand on the our baseline results for a given firm. Though our discussion indicates that the main driver of our findings is unlikely to be firm's changing credit demand, we should still be cautious before stating that these results indicate bank's varying collateral requirements.

In section 3.4, we provide some stylized facts on how collateral composition is related to firm characteristics. The main message is that highly rated, large, SOE firms face lower collateral requirements. If the composition of firms changes post 2008q4, such as there are more small, or lower rated, or non-SOE firms, then we might still observe rising shares of asset-based loans even if bank's collateral policy remain the same. Thus, we will further address the issue of varying firm composition in this subsection. Note that the previous empirical setting already addresses part of this issue. The most rigorous setting in Table 4 controls for firm*year-quarter fixed effects which could absorb any time-varying firm level variables. We are essentially comparing across different types of loans within each firm-year-quarter pair. Even if there are more small(lower rated, non-SOE) firms borrowing post 2008q4, the interpretation of the results would not be severely affected as the average pattern would be cancelled out. What's more, rating, size, and ownership fixed effects are included in all models in Table 4 and 5 which could control for the average difference for firms of different characteristics.

To further exclude the possible impact of varying firm composition post 2008q4, we perform more direct tests. First of all, for firm ownership, if our results are completely driven by the rising share of non-SOEs and banks still hold the same collateral policy for these firms over time, then limiting our sample to non-SOEs only, the baseline findings would not hold. [16] Second, if there are more small firms borrowing post 2008q4, possibly we would also observe rising shares of asset-based loans. To exclude this possibility, we drop all small firms from our sample. Lastly, there is one more dimension of firm characteristic that we should address, namely ratings. Though Figure 8 indicates that lower rated firms seem to rely slightly more on mortgage loans, regression analysis in Table 3 shows that rating does not significantly alters the probability or the share of asset-based borrowing. To further ensure robustness, we exclude all firms with rating below "B" from our sample.

[Insert Table 6 Here]

Table 6 reports the results that tackles with each of the above three issues. The odd columns use the same setting as column (5) in Table 4 and even columns correspond to the

[16]We limit the sample to non-SOEs instead of SOEs because the SOEs are only a very tiny part of our sample. Limiting to SOE observations only would not provide enough degree of freedom for estimation as our regression model includes loads of fixed effects.

coefficients in Table 5. Column (1) - (2), (3) - (4), and (5) - (6) deals with ownership, size, and rating, respectively. The findings in Table 6 are all consistent with our baseline results, indicating that our major findings are not driven by varying firm composition.

Overall, by controlling for various dimensions and different combinations of fixed effects, combined with direct tests of excluding relevant firm out of our sample, we show that varying firm composition is unlikely to be the main driver of our findings.

4.3 Government Expenditure Shock Related Industries?

China responds to the shock of GFC by rapidly rolling out an economic stimulus package, including both fiscal and credit stimulus policies. The fiscal policy stimulus, also known as the "Four trillion" economic stimulus plan, emphasizes massive government expenditure in target industries such as real state, infrastructure, and transportation. As shown in Figure 2, the volume share of loans issued to transportation, construction, and utility industries rises post 2008q4, which resonates with the stimulus policy. If these related industries tend to use more asset-based borrowing, then the government expenditure shock would also contaminate our baseline findings.

[Insert Table 7 Here]

To tackle possible confounding policy impacts, we adopt the following two criterion in determining the government expenditure shock related industries: (1) directly affected industries: transportation, construction, infrastructure, and real estate; (2) indirectly affected industries: sectors that operate along the production chain of the affected industries. Following Cong et al. (2019), the indirectly affected firms include those operating in the production of basic metals and non-metallic mineral products, as well as firms operating in mining and quarrying. We replicate Table 4 and Table 5 excluding the directly and indirectly affected firms. Table 7 reports the results and our results remain robust after excluding the shock related firms.

4.4 Heterogeneity Analysis

Collateral is required to mitigate the problem of default. During the GFC, the problem of information asymmetry exacerbates as banks become more uncertain about the future prospects of the firms given the rising uncertainty. Our baseline findings show that the bank responds by raising collateral requirements. However, we would also expect to observe heterogeneity among different firms as the shock might be unevenly distributed.

We consider two sources of heterogeneity in this subsection. First, state ownership would be very helpful in reducing uncertainty as it is naturally linked with government guarantee that limits the extent of downside risk. Previous researches also point out that the credit stimulus disproportionately favors SOEs and the government implicit guarantee becomes more prominent during GFC (Cong at al., 2019). Interest rate analysis as shown in Table A2 shows that SOEs are also charged with significantly lower interest rates post 2008q4, which provides further evidence for SOEs' being favored. With less downside risk, we would also expect banks to charge lower collateral requirements for SOEs. Second, firms operating in the foreign trade industry should be the worst hit as the GFC leads to dramatic shrinkage in global demand which constitutes the major source of profit for foreign trading companies. Other industries would also suffer from the shock but impact should be more indirect. Indeed, consistent with the higher risk, Table A2 shows that loans for foreign trading firms share a significantly higher rate post 2008q4, as compared to other firms. We would also expect there to be some differences in bank policies towards foreign trading firms and others.

[Insert Table 8 Here]

To see this, we define a dummy $Type$ that equals to 1 if the firm is a SOE (foreign trading firm) and 0 otherwise in column (1) - (2) ((3) - (4)) of Table 8. We then interact the $Type$ dummy with our previous loan type and time dummies and include the triple interaction terms to re-estimate the models in Table 5. The coefficients of the triple interaction terms then represent how the collateral structure of the relevant firms differs as compared to other firms post 2008q4. Column (1) - (2) in Table 8 present the heterogeneity analysis on SOEs. The results indicate that compared to non-SOEs, SOEs experienced significantly smaller rise in collateral requirements. The increases in the volume and volume share of asset-based loans post 2008q4 are less prominent for SOEs, which is consistent with our previous prediction.

Similarly, column (3) - (4) report the results for foreign trading firms. Compared to other firms, the volume share of unsecured loans dropped significantly more after 2008q4. The coefficients for asset-based loans related triple interaction terms are positive, though insignificant. Overall this indicates that loans for foreign trading firms become less earning-based post 2008q4, compared to other firms. Considering that foreign trade industry is the worst hit, it is natural to impose higher collateral requirement for these firms.

5 Other Dimensions on Bank Loan Policy

The baseline findings show that the volume and volume share of asset-based loans increase post 2008q4. The overall pattern is in support of rising collateral requirements imposed by banks. Aside from volume and collateral requirements, a typical loan contract includes other dimensions such as interest rate and maturity.

For interest rate, as we mentioned in section 2.3, the people's bank of China specifies the benchmark lending rate for bank loans and this usually constitutes the lower bound of lending rate. As part of the stimulus plan, the benchmark lending rate for loans with maturity between 6 months and 1 year was lowered from 7.47% to 5.31% and the left panels in Figure 3 all show a drastic drop in interest rate that perfectly aligns with the benchmark rate reduction. With the interest rate also being one margin of policy adjustments, we would not over-interpret on the average change in interest rate post 2008q4 (though the cross-sectional comparison still provides some interesting patterns, as we mentioned in the previous subsection by comparing different ownership and industries). We will instead discuss some other dimensions of bank loan policies in this subsection.

5.1 Maturity Shortening

Another commonly used approach to preserve the safety of debt is maturity shortening. As mentioned in Gorton et al. (2021), financial institutions create the possibility of fast withdrawal by shortening maturities during the crisis. This is also referred to as "flight from maturity". In the same spirit, banks could also shorten the maturity to retain the flexibility of withdrawing once things get worse. As unsecured loans are the most exposed to default risk, the option of maturity shortening would be especially tempting.

[Insert Table 9 Here]

Table 9 presents the regression analysis where we explore the extent of maturity shortening in our bank loan data. To better capture the magnitude, here we use the original loan level data instead of the firm level outstanding loan volume data as in the previous tables. The dependent variable is loan maturity. Control variables include the loan size (in log), bank share controls, industry share controls, rating FEs, size FEs, loan type FEs, and firm FEs. In column (1), the coefficient of *Post* indicates the average change in loan maturity post 2008q4, as compared to previously issued loans. The average maturity shortened by 0.037 year post 2008q4, which translates into about 0.44 month reduction. Among all loans, unsecured loans experienced the sharpest drop in loan maturity. Post 2008q4, the average maturity of unsecured loans shortened by 0.434 years. Given that the average loan maturity is only 0.71 years, the magnitude of maturity shortening is quite large. These findings are consistent with our prediction, suggesting that besides raising collateral requirements, banks also shortened the maturity for loans unprotected by collateral. The maturity shortening further strengthens firm's borrowing constraint and may induce them to forgo some profitable long term projects including R&D.

5.2 Relationship and Collateral: Substitutes?

The banking literature has long stressed that relationship between firms and banks could raise the availability of funding and reduce borrowing cost (Hoshi et al., 1990a, 1990b, 1991; Petersen and Rajan, 1994). Building relationship mitigates the information asymmetry problem between firms and banks. Meanwhile, collateralization is also believed to be a useful tool in resolving problems associated with asymmetric information (Chakraborty and Hu, 2006). In this sense, relationship could be considered as "soft collateral" and could function as substitute for collateralization. Indeed, as Boot and Thakor (1994) show, collateral requirements decline upon establishing relationship. Our findings indicate that on average there is higher requirement for collateral post 2008q4. We are then interested in whether pre-existing relationship may help relax the more stringent collateral constraint post 2008q4.

We first focus on the question of whether pre-existing relationship could raise the availability of funding and if yes, whether the fund raising power of relationship changes post 2008q4. The relationship analysis requires grouping the original loan level data to firm-year level data so that we could observe the total amount of new bank loans issued to a firm in each year. [17] To capture pre-existing relationship, we define dummy variable *Rela* that

[17] Quarterly data is inappropriate here as the quarter frequency is too short to capture the total loan

equals to 1 if the firm has borrowed from the bank in any of the previous years, and 0 otherwise. To facilitate comparison before and after the credit stimulus, we also define a time dummy $Post08$. Note that the data is annual instead of quarterly. We let $Post08$ to be equal to 1/4 in 2008, 1 afterwards, and 0 otherwise, in order to preserve consistency with the definition of $Post$ that equals to 1 for periods after 2008q4. [18]

[Insert Table 10 Here]

The regression results are in panel A of Table 10. The dependent variable in column (1) - (2) is the amount of new bank loans issued to a firm in each year. If a firm does not obtain any new loan in a given year, then the corresponding observation would not show up in the data. Thus, column (1) - (2) analyse how relationship is associated with loan volume conditional on obtaining bank loan. To explore the how relationship is associated with the probability of bank loan issuance, we define a dummy variable $1\{Newloan\}$ that equals to one if an old client obtains any new loan from the bank in the given year, and 0 otherwise. Old clients refers to the firms that borrowed from the bank for at least once in the previous years. Column (3) -(4) provide OLS analysis while column (5) - (6) apply Logit regression method. Aside from firm characteristic FEs, the odd columns also include firm FE. The positive estimated coefficient for $Rela$ is consistent with the banking literature, showing that pre-existing relationship not only raises the probability of obtaining bank loan, but also the volume conditional on loan issuance. Nevertheless, the coefficients for $Rela * Post08$ are negative in column (3) - (6) and the magnitude outsizes the coefficients of $Rela$. This means that post 2008, pre-existing relationship could no longer help improving the probability of obtaining bank loan. Conditional on bank loan issuance, the existence of relationship also adds to weakly less loan volume post 2008, as indicated by the negative (though insignificant in column (2)) coefficients in column (1) - (2).

Panel A shows that relationship could improve both the probability and the volume of funding in normal times, but its power significantly weakens post 2008. These indicate that while allocating the funding during the credit stimulus, relationship is no longer an important determinant for the bank. But could it be possible that banks apply different policies for

issuance to a firm.

[18] We also try define $Post08$ as a dummy that equals to 1 for 2008 and afterwards, and 0 otherwise. Results remain robust

different firms? For example, for old clients, banks sustain their previous collateral policy while it raises collateral requirements for new clients. To see this, we drop all firms that entered our sample after 2008q4 (new clients) and leave only those who borrowed at least once before 2008q4 (old clients). If relationship could act as a substitute for collateral, we would observe weaker or even no shift from earnings-based loans to asset-based loans among these old clients. Panel B in Table 10 follows the same setting as in Table 6 and presents the regression results which are still highly consistent with the baseline findings. Firms with pre-existing relationship still face higher collateral requirements post 2008q4, providing no evidence for the substitutability between collateral and relationship.

Taken together, the relationship analysis shows that: (1) relationship raises the availability of funding during normal times but not so post 2008. (2) we find no evidence in support of relationship acting as a substitute for collateral post 2008q4.

6 Further Analysis

Our previous analysis show that bank raises collateral requirements under the tension of rising economic uncertainty and mandatory credit expansion. This motivates us to move one step further and explore the following question: how would firms respond to bank's changing collateral requirements?

Campello and Hackbarth (2012) point out that the availability of financing, rather than the availability of investment opportunities, drives firms' investment spending and asset tangibility matters for relaxing borrowing constraints. Thus, tighter collateral requirements might induce firms to prioritize investment in real estates over intangible investments in order to facilitate future funding. Unsecured and guaranteed loans relies only on firm's creditworthiness and its future earnings. Reduced access to these earning-based loans would reduce firm's incentives to make R&D investments which could raise future earnings but requires substantial funding in initial periods. As patents are rarely used as collateral in China, R&D investments do not facilitate collateralized borrowing. Facing tighter collateral constraint, firms in more urgent need of bank loans might be more likely to refrain from making R&D investments and thus would produce less applications for patents.

What's more, further dissecting collateral composition, we can see that mortgage collateral is mostly real estate for manufacturing purposes and other fixed assets are rarely used.

In terms of pledge loans, the collateral is mostly banker's acceptance bills and RMB certificates of deposit, both of which require depositing money (as margin in the case of banker's acceptance bills) into a bank in exchange for the financial security. As investments in real estate usually requires investing larger amounts for a longer term, we would expect that rising shares in mortgage loans would lead to more substantial reduction in R&D investments and patent applications, as compared to pledge loans. [19]

To test the above predictions, we need to obtain firm-level balance sheet and patent application data. Our bank loan data includes the name of the firm which makes it possible to merge with 2006-2013 Chinese Annual Survey of Industrial Enterprises (ASIE) data that includes detailed firm balance sheet statistics. Based on the merged data, we can then obtain patent application records following China Patent Database Project. [20]. Note that ASIE data is essentially a survey for large and medium firms while our data covers mostly small and medium enterprises. Not surprisingly, there would be substantial loss in observations and the loss would be disproportionately concentrated in small firms. Indeed, only 800 firms remain post merging.

Firms might be deferentially exposed to the loan policy change and its response would also differ. To capture the cross-sectional differences, we focus on the firms that experienced shift towards asset-based loans in collateral structure post 2008. To see this, we first compute the change in the outstanding volume share of asset-based loans pre- and post- 2008q4 for each firm. We then define a dummy variable $Posi$ that equals to 1 for firms that have increased volume share of asset-based loans. Comparing across the $Posi$ firms and the rest, we are then able to capture cross-sectional differences in patent applications for firms of various exposure to bank loan policy change.

[Insert Table 11 Here]

Table 11 reports the regression results. Column (1) - (2), (3) - (4), and (5) - (6) defines Top according to the volume share change of asset-based loans, mortgage loans, and pledge

[19]We did not focus on the change in fixed investments as real estate for manufacturing purposes only accounts for part of fixed assets. Other assets, such as machines, vehicles, are also included as fixed asset but do not contribute to collateralized borrowing. Thus, fixed investment would be a noisy proxy for firm total investment in mortgage collateral. As for the change in intangible asset investment, the data is usually missing.

[20]https://sites.google.com/site/sipopdb

loans, respectively. The dummy variable $Post08$ is defined in the same way as in panel A Table 9, which captures the time series difference. The dependent variables include total patent applications (column (1) - (3)) and to see the possible impact on production efficiency, we also try TFP in column (4) - (6). [21] Control variables are firm age ($Ln(Age+1)$), firm size ($Ln(Asset)$, return on asset (ROA), liquidity ratio ($LiquidR$), and industry competition (HHI). We also include firm and year fixed effects. The variable of interest here is $Posi*Post08$, the coefficient of which indicate how the dependent variables differ for firms affected by bank loan policy change, as compared to others.

The results in column (1) show that firms with loan structure shifting from earning-based loans to asset-based loans post 2008q4 also apply for significantly less patents. Further differentiating between mortgage and pledge loans, we can see that the negative outcome concentrates among firms with rising mortgage shares. These are consistent with idea that firms cater to bank loan policy change and prioritize real estate investment over R&D. As for pledge loans, firms that increase pledge loan borrowing post 2008q4 even apply for slightly more patents as compared to other firms post 2008q4. As pledge loans require liquid short-term financial securities as collateral, its negative impact on relatively longer term investments should be more limited. Besides, firms that would be granted banker's acceptance bills even post the crisis should be relatively less risky in the first place, and this might account for the positive outcome on patent applications. The positive significance, however, is not robust to different empirical settings such as including other fixed effects. For this reason, we would not spend too much time deciphering the positive coefficient here.

Column (4) - (6) present the results on TFP. The estimated coefficients are all insignificant, though again the coefficient is negative if we focus on the firms with rising mortgage share. As TFP is a relatively opaque measure and the reduction in R&D investment may take some time to show real impacts on production efficiency, the insignificant coefficients may also be plausible. Note that we should be cautious in interpreting the findings here. Though the empirical results are consistent with the possibility of firms' catering to bank's loan policy, we are not ascertaining the causal relationship here.

To summarize, the firm level analysis indicates that for firms that experienced increases in asset-based loan volume share, they also witnessed declines in patent applications. This effect is more prominent among firms that have significantly more mortgage loans post 2008.

[21] TFP is computed following Olley and Pakes (1996)

Overall, these findings are consistent with the story that bank loan policy change might have some real impacts and could induce firms to prioritize real estate investments over R&D. The reduction in patent applications may affect production efficiency in a longer term.

7 Conclusion

Using a unique and detailed loan level dataset, this paper first provides an overview of the Chinese bank loan collateral structure and its determinants. The average volume ratio of earnings-based loans and asset-based loans is about 1:1 but the collateral structure depends on certain firm characteristics. State-owned large firms with high ratings obtain more unsecured loans while loans by large firms with low ratings resort to guarantee by third parties. Small firms, especially the private ones, however, have to rely on mortgage loans regardless of their ratings.

This paper then investigates how loan collateral structure responds to the tremendous stimulus package mostly in the form of mandatory credit expansion after the Lehman collapse. Under the tension of rising economic uncertainty and credit expansion mandate, banks raise collateral requirements and the loan structure shifts towards asset-based loans. Meanwhile, there is also significant maturity shortening. Pre-existing relationship raises the availability of funding during normal times but its impact weakens post the GFC. Consistent with the story that bank collateral policy change may induce firms to prioritize real estate investment (as better collateral) and reduce R&D, this paper finds that firms with increased share of asset-based loans also apply for significantly less patents, especially so for mortgage loans.

In light of the theoretical developments in the last decade, recent empirical literature starts to explore the collateral structure, as well as its implications for monetary policy transmission (Lian and Ma, 2021; Caglio et al., 2021; Ivashina et al., 2021). The money and credit creation in an economy crucially hinge on its underlying collateral structure. The paper also shows that monetary easing during downturn also changes the collateral structure as required by banks, which in turn has important implications for resource misallocation. Overall, our findings shed light on how credit gets created and allocated in China over the GFC.

The findings may help us better understand the dynamics of China's economy. Before

2012, China had kept a two-digit GDP growth rates for many years. China's economic growth took a great hit ever since then. The results also pinpoint to other salient facts on China's economy post the crisis: a housing boom, surging debt levels, substantial TFP growth slowdown and TFP dispersion across firms and regions. To the extent that land and real estates presumably have been the most important collateral for China's growth in the last two decades, the economic stimulus has made China's financial system fragile, as suggested by the recent Evergrande default episode. This resonates with the insight of Kiyotaki and Moore (2002) that a key difference in postwar Japan and the United States is that Japan relies on bank loans secured by fixed assets while U.S. firms borrow against future earnings. The reliance on asset-based loans renders Japan's economy vulnerable to fluctuations in asset prices. The U.S. economy, on the other hand, is less sensitive to asset price changes. Nevertheless, it has taken decades for the U.S. to transition from a mostly asset-based credit system to a mostly earning-based credit system (Benmelech et al., 2020). It seems that China still has a long way to go in terms of financial development. And this matters a lot for its future.

References

Alfaro, L., García-Santana, M., & Moral-Benito, E. (2021). On the direct and indirect real effects of credit supply shocks. *Journal of Financial Economics*, 139(3), 895-921.

Amiti, M., & Weinstein, D. E. (2018). How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data. *Journal of Political Economy*, 126(2), 525-587.

Asriyan, V., Laeven, L., & Martın, A. (2020). Collateral Booms and Information Depletion. *The Review of Economic Studies*, rdab046

Bai, C. E., Hsieh, C. T., & Song, Z. M. (2016). The long shadow of a fiscal expansion (No. w22801). *National Bureau of Economic Research*.

Benmelech, E., Kumar, N., & Rajan, R. (2020). The decline of secured debt (No. w26637). *National Bureau of Economic Research*.

Bernanke, B. S., & Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4), 27-48.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, 1, 1341-1393.

Boot, A. W., & Thakor, A. V. (1994). Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game. *International Economic Review*, 899-920.

Buera, F. J., Kaboski, J. P., & Shin, Y. (2011). Finance and development: A tale of two sectors. *American Economic Review*, 101(5), 1964-2002.

Caglio, C. R., Darst, R. M., & Kalemli-Özcan, S. (2021). Risk-Taking and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms (No. w28685). *National Bureau of Economic Research.*

Campello, M., & Hackbarth, D. (2012). The firm-level credit multiplier. *Journal of Financial Intermediation*, 21(3), 446-472.

Chakraborty, A., & Hu, C. X. (2006). Lending relationships in line-of-credit and nonline-of-credit loans: Evidence from collateral use in small business. *Journal of Financial Intermediation*, 15(1), 86-107.

Chen, Z., He, Z., & Liu, C. (2020). The financing of local government in China: Stimulus loan wanes and shadow banking waxes. *Journal of Financial Economics*, 137(1), 42-71.

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.

Cong, L. W., Gao, H., Ponticelli, J., & Yang, X. (2019). Credit allocation under economic stimulus: Evidence from China. *The Review of Financial Studies*, 32(9), 3412-3460.

Crouzet, N., & Eberly, J. (2018, May). Intangibles, investment, and efficiency. *In AEA Papers and Proceedings* (Vol. 108, pp. 426-31).

Diamond, D. W., Hu, Y., & Rajan, R. G. (2020). Pledgeability, industry liquidity, and financing cycles. *The Journal of Finance*, 75(1), 419-461.

Geanakoplos, J. (2010). The Leverage Cycle. *NBER Macroeconomics Annual*, 24(1), 1-66.

Gorton, G., Metrick, A., & Xie, L. (2021). The flight from maturity. *Journal of Financial Intermediation*, 47, 100872.

Gorton, G., & Ordonez, G. (2014). Collateral crises. *American Economic Review*, 104(2), 343-78.

Hart, O., & Moore, J. (1994). A theory of debt based on the inalienability of human capital. *The Quarterly Journal of Economics*, 109(4), 841-879.

Hart, O., & Moore, J. (1998). Default and renegotiation: A dynamic model of debt. *The Quarterly Journal of Economics*, 113(1), 1-41.

Hau, H., & Ouyang, D. (2018). Capital Scarcity and Industrial Decline: Evidence from 172 Real Estate Booms in China. *Swiss Finance Institute Research Paper*, 38.

Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, 112(3), 663-691.

Hoshi, T., Kashyap, A., & Scharfstein, D. (1990a). Bank Monitoring and Investment: Evidence from the Changing Structure of Japanese Corporate Banking Relationships. *Asymmetric Information, Corporate Finance, and Investment*, 105-126.

Hoshi, T., Kashyap, A., & Scharfstein, D. (1990b). The Role of Banks in Reducing the Costs of Financial Distress in Japan. *Journal of Financial Economics*, 27(1), 67-88.

Hoshi, T., Kashyap, A., & Scharfstein, D. (1991). Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups. *Quarterly Journal of Economics*, 106(1), 33-60.

Hsieh, C. T., & Song, Z. M. (2015). Grasp the large, let go of the small: The transformation of the state sector in China (No. w21006). *National Bureau of Economic Research.*

Huang, Y., Pagano, M., & Panizza, U. (2020). Local crowding-out in China. *The Journal of Finance*, 75(6), 2855-2898.

Ivashina, V., Laeven, L., & Moral-Benito, E. (2021). Loan Types and the Bank Lending Channel. *Journal of Monetary Economics.*

Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3), 319-338.

Jiménez, G., Mian, A., Peydró, J. L., & Saurina, J. (2020). The real effects of the bank lending channel. *Journal of Monetary Economics*, 115, 162-179.

Kashyap, A. K., & Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy?. *American Economic Review*, 90(3), 407-428.

Kashyap, A. K., Stein, J. C., & Wilcox, D. W. (1993). Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance. *The American Economic Review*, 83(1), 78-98.

Keil, J., & Müller, K. (2020). Bank branching deregulation and the syndicated loan market. *Journal of Financial and Quantitative Analysis*, 55(4), 1269-1303.

Kermani, A., & Ma, Y. (2021). Two Tales of Debt. *Working Paper*

Khwaja, A. I., & Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4), 1413-42.

Kiyotaki, N., & Moore, J.(1997). Credit cycles. *Journal of Political Economy*, 105(2).

Kiyotaki, N., & Moore, J. (2002). Balance-sheet contagion. *American Economic Review*, 92(2), 46-50.

Lian, C., & Ma, Y. (2021). Anatomy of corporate borrowing constraints. *The Quarterly Journal of Economics*, 136(1), 229-291.

Lorenzoni, G. (2008). Inefficient credit booms. *The Review of Economic Studies*, 75(3), 809-833.

Mendoza, E. G. (2010). Sudden stops, financial crises, and leverage. *American Economic Review*, 100(5), 1941-66.

Midrigan, V., & Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, 104(2), 422-58.

Moll, B. (2014). Productivity losses from financial frictions: Can self-financing undo capital misallocation?. *American Economic Review*, 104(10), 3186-3221.

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6), 1263-1297.

Petersen, M. A., & Rajan, R. G. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. *The Journal of Finance*, 49(1), 3-37.

Song, Z., Storesletten, K., & Zilibotti, F. (2011). Growing like china. *American Economic Review*, 101(1), 196-233.

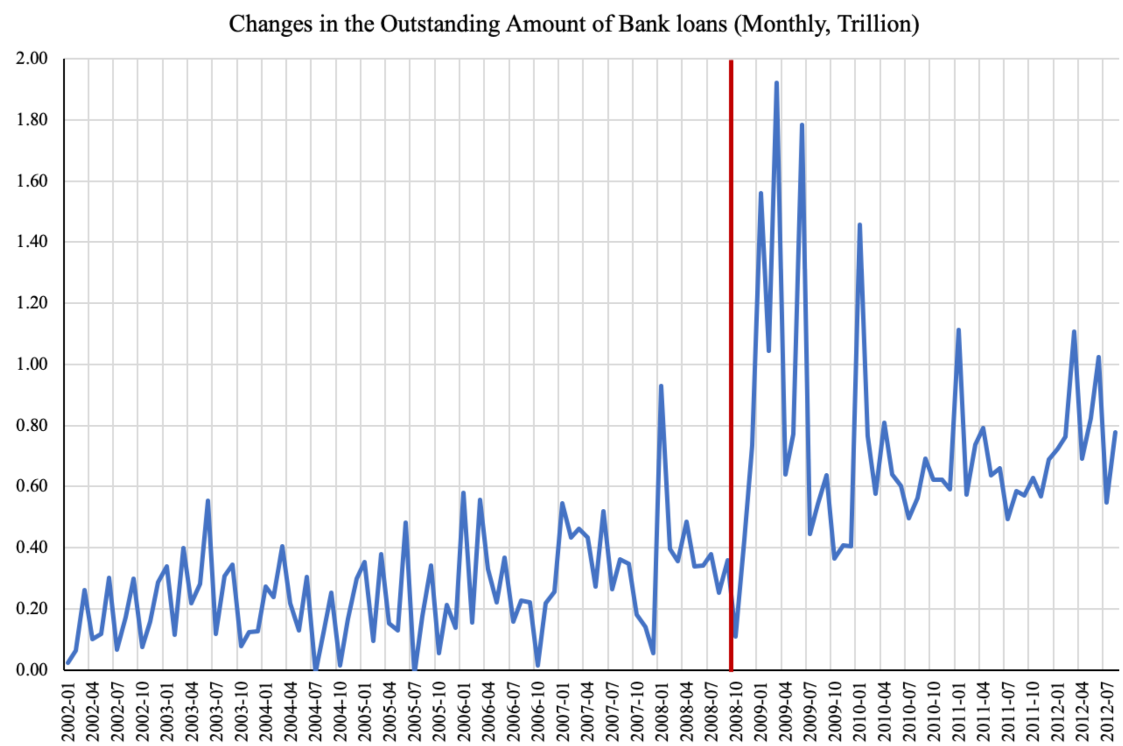
Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3), 393-410.

Figures

Figure 1: Outstanding Bank Loan Volume

This figure presents the outstanding bank loan volume for each quarter. Panel A shows the changes in the total outstanding bank loan volume from the total social financial data of the People's Bank of China while panel B presents the outstanding bank loan volume at each quarter end calculated from our bank loan data. At each quarter end, we aggregate the outstanding volume of bank loans using our bank loan data. The numbers thus reflect the total outstanding bank loan issued by the bank in the specific prefecture city.

Panel A.



Panel B.

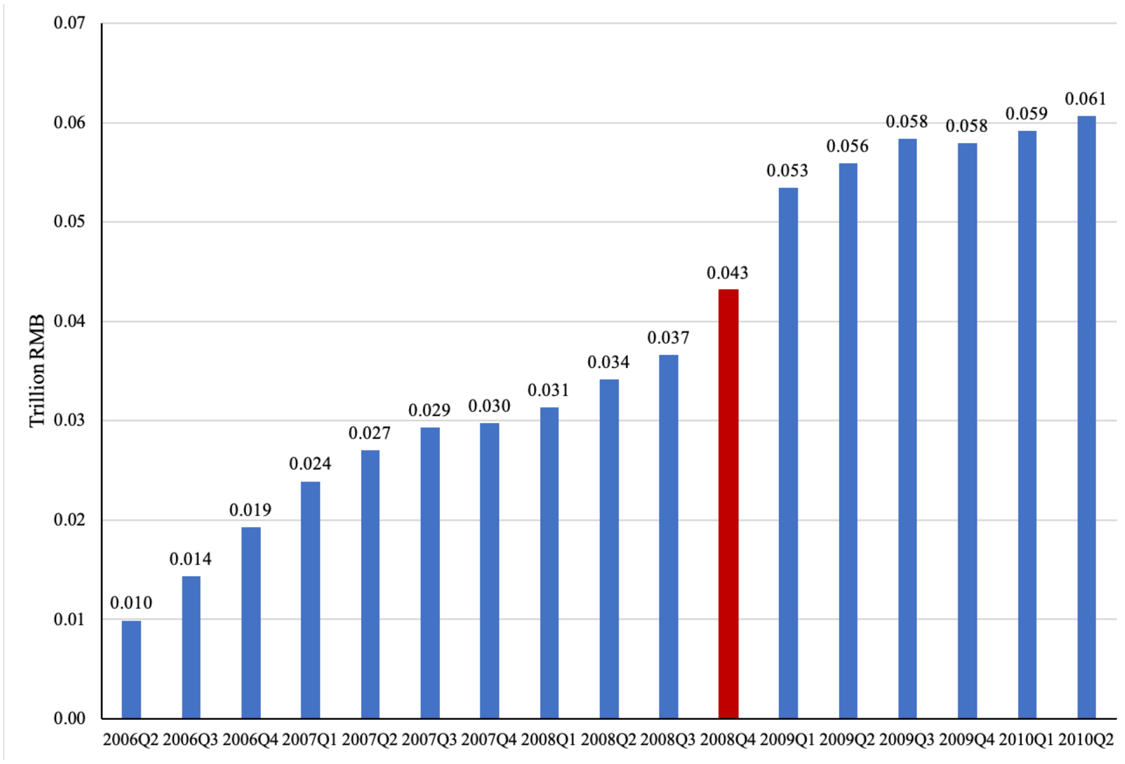

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Figure 2: Value Shares of Loans to Different Industries

This figure shows the value shares of loans that flow to different industries. Our sample include loans to over 23 industries. For ease of presentation, we first group industries into four buckets: (i) service; (ii) Manufacturing; (iii) Transportation, Construction, and Utility; (iv) Others. We then compute the value of loans for each industry buckets as a percentage of total value of loans in each quarter.

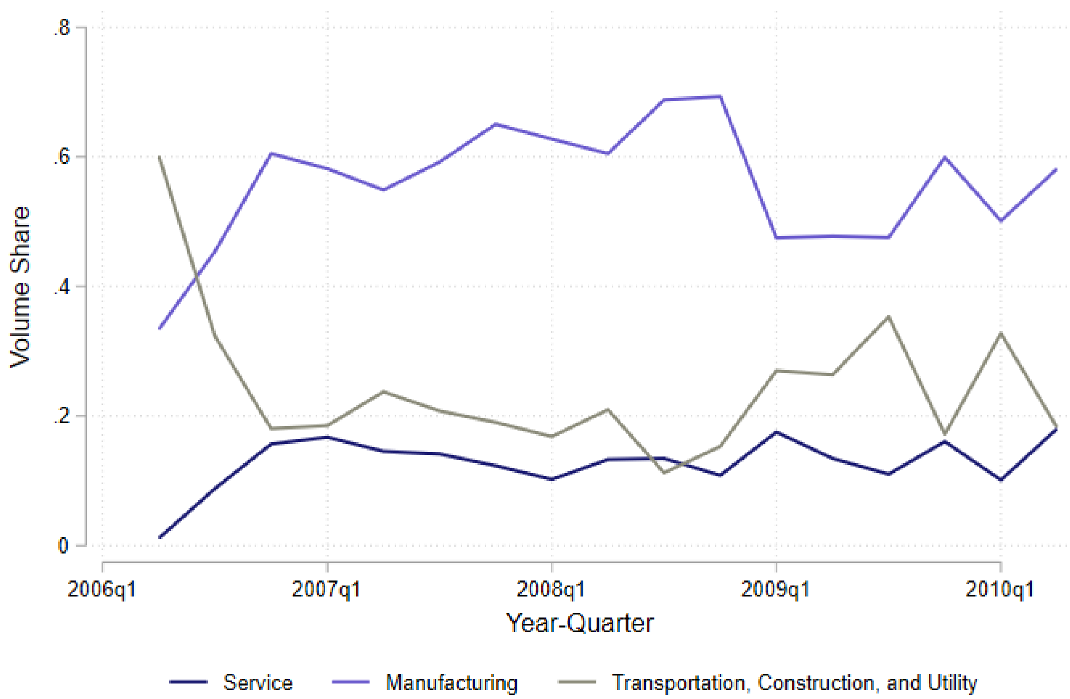
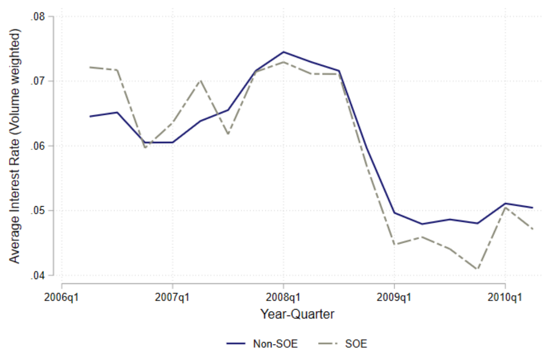
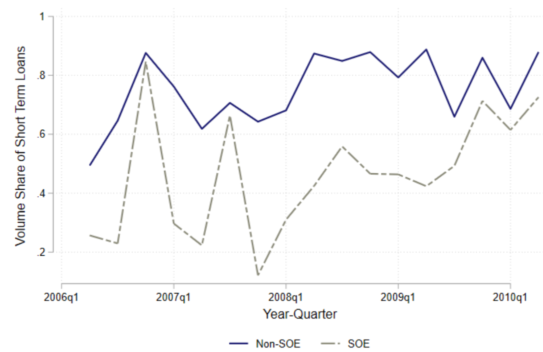


Figure 3: Rate and Maturity Distribution for Different Firms

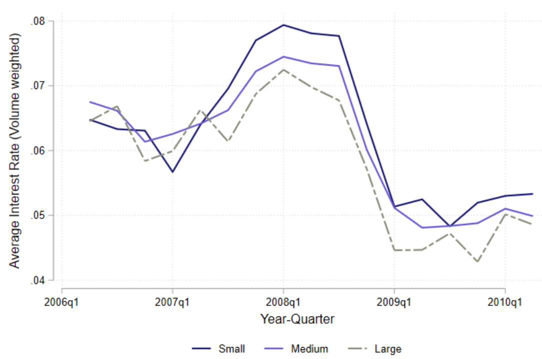
This figure presents the volume weighted average interest rate and maturity distribution for firms grouped by ownership ((a) - (b)), size ((c) - (d)), and rating ((e) - (f)). Panel (a), (c), and (e) are for average interest rate and penel (b), (d), and (f) are for maturity distribution. For the maturity distribution, we compute the value share of short-term loans,i.e., loans with maturity less than one year.



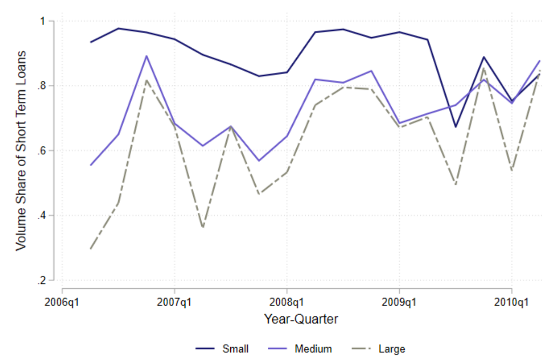
(a) Average Rate (Ownership)



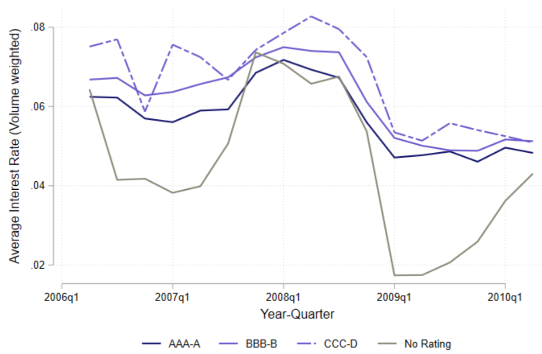
(b) Value Share of Short-Term Loans (Ownership)



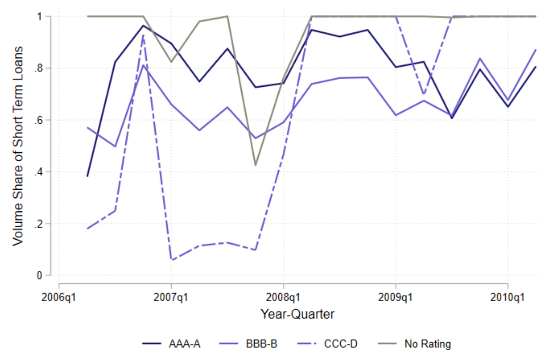
(c) Average Rate (Size)



(d) Value Share of Short-Term Loans (Size)



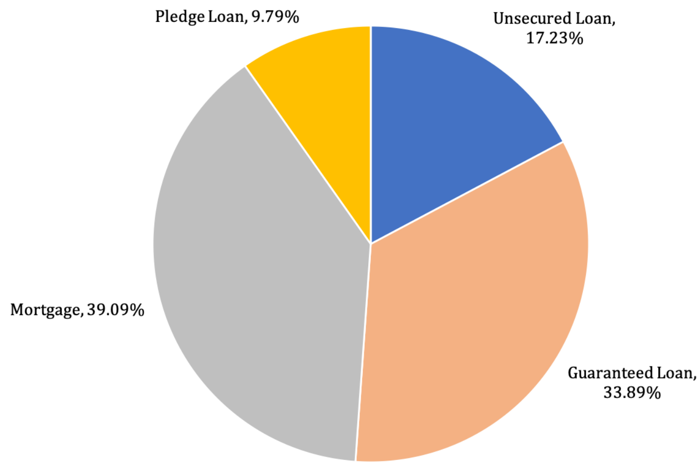
(e) Average Rate (Rating)



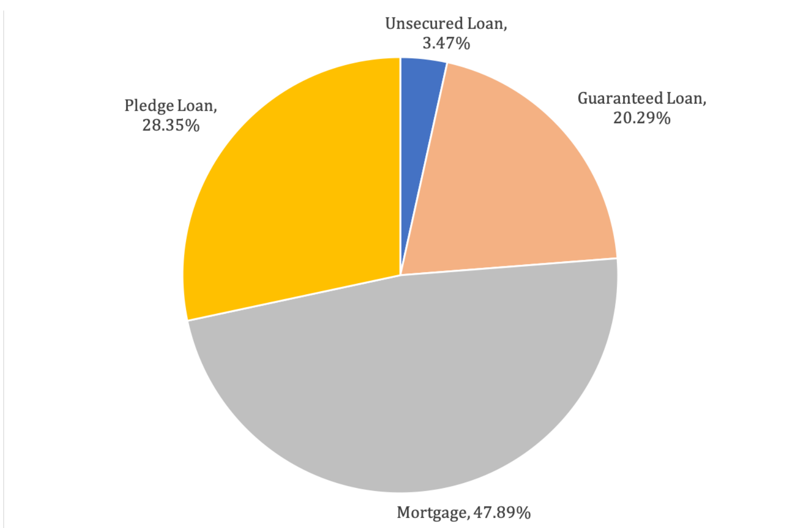
(f) Value Share of Short-Term Loans (Rating)

Figure 4: Bank Loan Structure

This figure presents the structure of bank loans. We show the composition of different types of loans in our sample, that is, unsecured, guaranteed, mortgage, and pledge loans. Panel (a) depicts the volume share while panel (b) presents the shares in terms of loan number.



(g) By Loan Volume



(h) By Loan Number

Figure 5: Bank Loan Type and Maturity Distribution

This figure shows the maturity distributions for the four types of loans. For ease of presentation, we group loans into five maturity buckets: 1 day - 1 month, 1 month - 3 months, 3 months - 6 months, 6 months - 1 year, 1 year and above. For each type of bank loans, we first aggregate the volume of loans in each maturity bucket and normalize it with the total volume for that type. The resulting numbers are the maturity distribution for each type of bank loans.

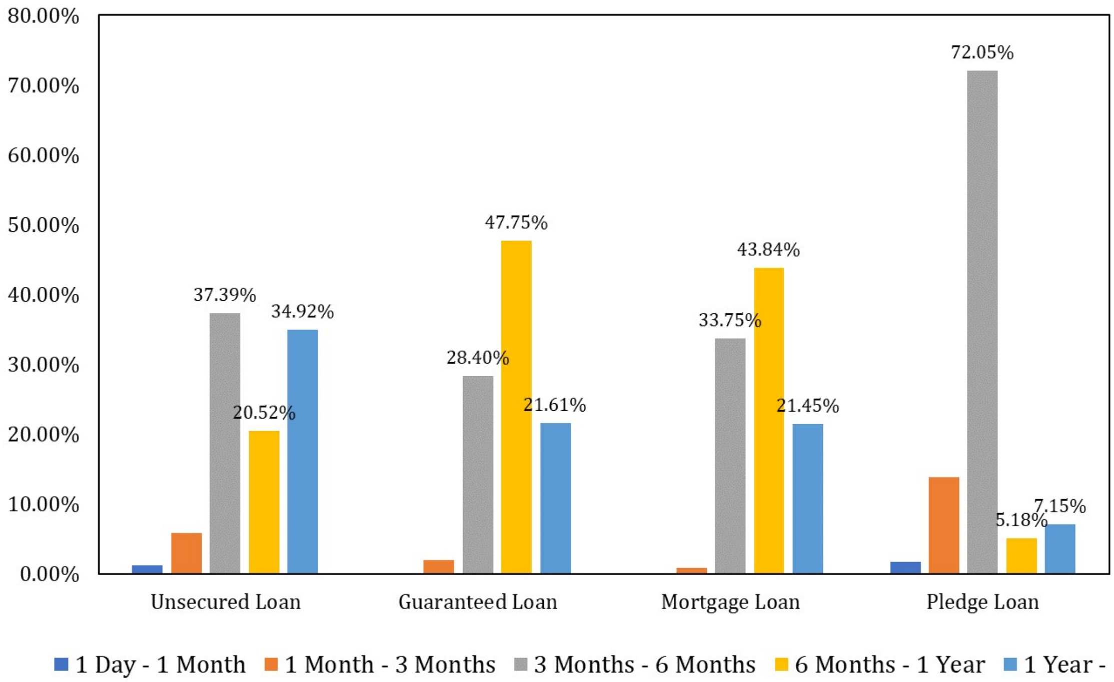


Figure 6: Collateral Composition by Firm Ownership

This figure explores the collateral composition for firms of different ownership structure. First, we aggregate the total bank loan volume separately for SOEs and Non-SOEs. Within each ownership group, we the compute the total loan volume for different types of bank loans. We report the volume shares of different types of bank loans for SOEs and Non-SOEs in the following figure.

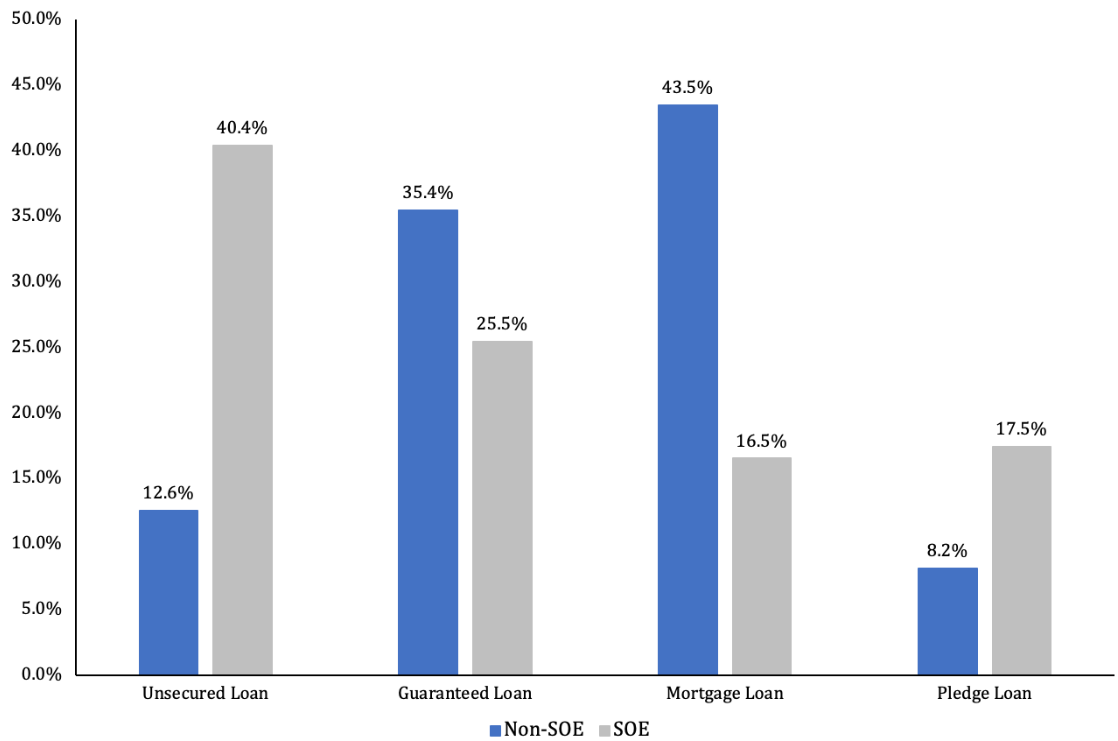


Figure 7: Collateral Composition by Firm Size

This figure explores the collateral composition for firms of different size. First, we aggregate the total bank loan volume separately for small, medium, and large firms. Within each size group, we then compute the total loan volume for different types of bank loans. We report the volume shares of different types of bank loans for each size group in the following figure.

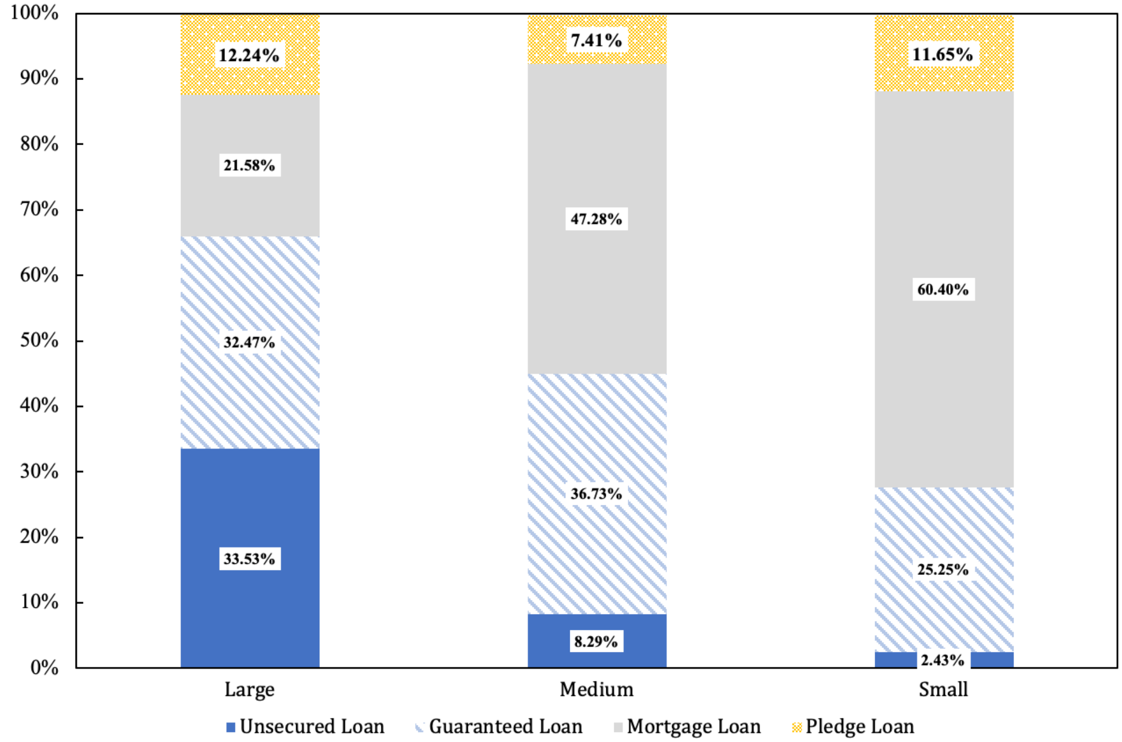
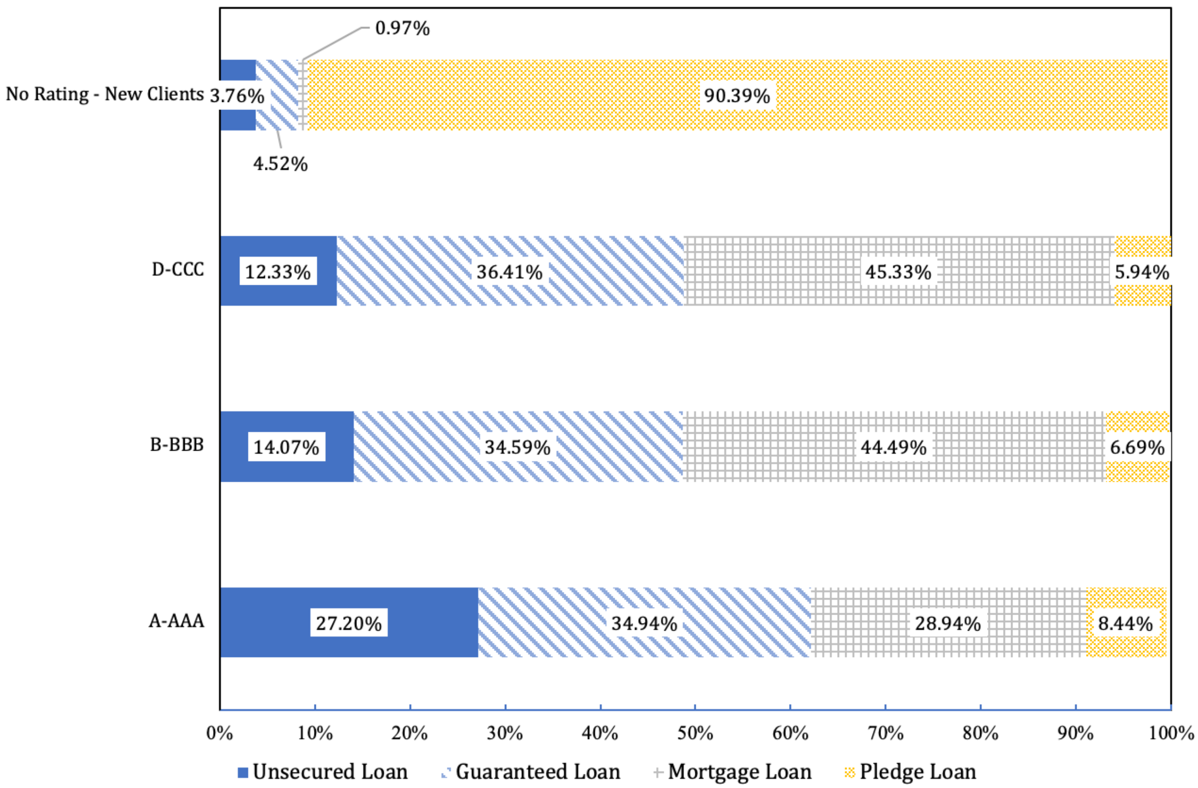


Figure 8: Collateral Composition by Rating

This figure explores the collateral composition for firms of different rating. First, we aggregate the total bank loan volume separately for firms in different rating buckets (AAA-A, BBB-B, CCC-D, No rating). Within each rating bucket, we then compute the total loan volume for different types of bank loans. We report the volume shares of different types of bank loans in each rating bucket in the following figure.



Tables

Table 1: Summary Statistics on Bank Loan

This table presents the summary statistics on the bank loan data. Panel A includes the summary statistics on loan volume, interest rate, and maturity for the whole sample. Panel B further classifies bank loans according to firm's ownership structure, firm size, and rating.

Panel A.

Variables		Mean	s.d.	Min	P5	P25	P50	P75	P95	Max
Loan Volume (Milion, RMB)	Loan Size	5.13	16.20	0.00	0.10	0.50	1.50	4.50	20.00	800.00
	Special Mention	0.16	3.78	0.00	0.00	0.00	0.00	0.00	0.00	400.00
	Substandard	0.01	0.27	0.00	0.00	0.00	0.00	0.00	0.00	10.10
	Doubtful	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	3.00
	Loss	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	3.30
Interest Rate (%)		5.66	1.76	1.47	2.30	4.80	5.84	6.93	8.22	17.56
Maturity (Year)		0.71	0.82	0.01	0.18	0.44	0.50	0.99	1.00	19.00

Panel B.

Loan Value (Million, RMB)		Total Volume (Share)	Loan Number (Share)	Mean	s.d.	Median
Ownership	Non-SOE	136225.86 (83.45%)	29626 (93.17%)	459.82	1427.36	150.00
	SOE	27018.33 (16.55%)	2171 (6.83%)	1244.51	3173.86	186.77
Size	Large	61948.30 (37.95%)	4216 (13.26%)	1469.36	3676.53	494.00
	Medium	82531.21 (50.56%)	16106 (50.65%)	512.43	1101.19	200.00
	Small	18764.68 (11.49%)	11475 (36.09%)	163.53	385.02	100.00
Rating	AAA-A	43254.5 (26.5%)	6162 (19.38%)	701.96	2096.96	173.50
	BBB-B	110272.21 (67.55%)	22642 (71.21%)	487.03	1526.53	170.00
	CCC-D	4640.87 (2.84%)	452 (1.42%)	1026.74	2182.55	200.00
	No Rating	5076.60 (3.11%)	2541 (7.99%)	199.79	580.91	34.00

Table 2: Details on Guarantors, Mortgage, and Pledged Collateral

This table provides details on the composition of guarantors (panel A), mortgage collateral (panel B), and pledged assets (panel C) for different types of loans.

Panel A. Details on Guarantors

Guarantor	No. of Loans	Percentage
Large State-owned firms	85	1.32%
Other firms	5265	81.59%
Commercial banks and policy banks	204	3.16%
Foreign banks or sino-foreign equity joint bank	1	0.02%
Foreign or sino-foreign equity joint nonbank financial institutions	12	0.19%
Other nonbank financial institutions	49	0.76%
Other Guarantors	210	3.25%
Missing	627	9.72%
Total	6453	100.00%

Panel B. Details on Mortgage Collateral

Mortgage Collateral Type	No. of Loans	Percentage
Real estate (for manufacturing purpose)	13534	88.88%
Residential real estate	302	1.98%
Chattel mortgage	173	1.14%
Others	204	1.34%
Missing	1014	6.66%
Total	15227	100.00%

Panel C. Details on Pledged Collateral

Pledged Financial Assets	No. of Loans	Percentage
Banker's acceptance	5978	66.31%
Commercial acceptance	358	3.97%
RMB certificates of deposit	454	5.04%
Foreign certificates of deposit	20	0.22%
Foreign Exchange	14	0.16%
Soverign bonds	1	0.01%
Financial bonds	3	0.03%
Other securities	252	2.8%
Others	606	6.72%
Missing	1329	14.74%
Total	9015	100.00%

Table 3: Determinants of Collateral Composition

This table presents the regression results on the determinants of firm's collateral composition. For each firm at the end of each quarter, we first aggregate the total outstanding bank loan volume and then separately compute the outstanding volume for each type of bank loan. We then obtain the value shares of each type of bank loan for each firm at each quarter-end and these shares are the dependent variables in the odd columns. Note that the value shares are bounded with in the range of (0,1). To address this problem, we redefine a corresponding dummy variable that equals to one if the value share is positive and 0 otherwise. Using these dummy variables as dependent variables, we then perform logit analysis and present the results in even columns. The dependent variables include dummy variables on ownership structure (SOE), rating (High, Medium), and size (Large, Medium).

		Unsecured Loan		Guaranteed Loan		Mortgage Loan		Pledge Loan	
		Loan Share (OLS) (1)	Logit (2)	Loan Share (OLS) (3)	Logit (4)	Loan Share (OLS) (5)	Logit (6)	Loan Share (OLS) (7)	Logit (8)
Ownership	SOE	0.135***	1.278***	-0.032	-0.276	-0.117**	-0.719***	0.011	0.312
		(3.29)	(3.77)	(-0.59)	(-1.09)	(-2.17)	(-2.64)	(0.42)	(0.92)
Rating	High (AAA-A)	0.060***	1.421**	-0.107*	-0.621**	-0.009	-0.165	0.052***	0.881
		(2.59)	(2.54)	(-1.73)	(-2.16)	(-0.15)	(-0.51)	(2.62)	(1.61)
	Medium (BBB-B)	0.027	0.562	-0.100*	-0.544*	0.045	0.097	0.025	0.445
		(1.35)	(1.09)	(-1.68)	(-1.96)	(0.76)	(0.31)	(1.43)	(0.83)
Size	Large	0.125***	3.090***	0.172***	0.952***	-0.308***	-1.366***	0.011	0.475**
		(5.42)	(9.40)	(4.51)	(5.54)	(-8.41)	(-7.12)	(0.67)	(2.10)
	Med	0.026***	1.892***	0.100***	0.647***	-0.134***	-0.517***	0.007	0.293**
		(4.54)	(6.56)	(5.41)	(6.93)	(-7.15)	(-5.36)	(1.35)	(2.07)
Industry * Year-Quarter FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N		20453	19688	20453	20446	20453	20452	20453	19173
R2(Pseudo R2)		0.208	0.28	0.061	0.043	0.155	0.122	0.097	0.108

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 4: Baseline Analysis on Loan Volume

This table presents the regression results for $Ln(1 + LoanVol_{i,k,q}) = \sum_{k=G,M,P} \alpha_{k1} Post_q * Loantype_k + \sum_{k=G,M,P} Controls * Loantype_k + Controls + FEs + \epsilon_{i,k,q}$. The dependent variable is the outstanding loan volume for firm i of loan type k by the end of quarter q (in log). $Post_q$ is a dummy variable that equals to 1 if quarter q is post or equal to 2008q4, and 0 otherwise. $Loantype_k$ is a dummy variable that equals to 1 for observations of loan type k and 0 otherwise. Control variables include bank branch share and industry share controls. All controls are interacted with loan type dummies to allow for heterogeneous effects on different loan types. Rating*loan type, size*loan type, and firm ownership * loan type fixed effects are included in all regressions. Column (2) and (3) further includes year-quarter and firm fixed effects, respectively. In column (4) we control for both firm and year-quarter fixed effects. And the last column is the most strict setting which controls for firm*year-quarter fixed effects.

	$Ln(1 + LoanVol_{i,k,q})$				
	(1)	(2)	(3)	(4)	(5)
Guaranteed ∗ Post	-0.063	-0.063	-0.014	-0.014	-0.014
	(-0.70)	(-0.70)	(-0.23)	(-0.23)	(-0.23)
Mortgage ∗ Post	0.354***	0.354***	0.558***	0.558***	0.558***
	(4.18)	(4.18)	(9.42)	(9.42)	(9.43)
Pledge ∗ Post	0.115**	0.115**	0.087**	0.087**	0.087**
	(2.07)	(2.07)	(1.97)	(1.97)	(1.97)
Post	0.075*		-0.003		
	(1.86)		(-0.08)		
Constant	2.156***	2.153***	2.288***	2.159***	1.049
	(7.77)	(7.91)	(2.81)	(2.73)	(0.87)
Branch Share Control	✓	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓	✓
*Rating*Loan Type FE*	✓	✓	✓	✓	✓
*Size*Loan Type FE*	✓	✓	✓	✓	✓
*Ownership*Loan Type FE*	✓	✓	✓	✓	✓
Firm FE			✓	✓	
Year-quarter FE		✓		✓	
*Firm * Year-quarter FE*					✓
N	81968	81968	81180	81180	81180
Adjusted R^2	0.393	0.393	0.882	0.883	0.905

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 5: Baseline Analysis on Loan Volume Share

This table shows the regression results for $VolShare_{i,k,q} = \beta_k Post_q + Controls + FEs + \epsilon_{i,k,q}$. We run the regression separately for the four types of bank loans. The dependent variable is outstanding volume share of each type of loan for firm i by the end of quarter q. $Post_q$ is a dummy variable that equals to 1 if quarter q is post or equal to 2008q4, and 0 otherwise. Control variables include bank and industry share controls, size fixed effects, rating fixed effects, firm ownership fixed effects, and firm fixed effects.

	Fraction of:			
	Unsecured Loan (1)	Guaranteed Loan (2)	Mortgage Loan (3)	Pledge Loan (4)
Post	-0.007**	-0.028***	0.038***	0.001
	(-2.24)	(-4.55)	(6.00)	(0.29)
Constant	0.114	0.170	0.716***	0.023
	(1.57)	(1.51)	(5.03)	(0.46)
Branch Share Control	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Size FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N	20295	20295	20295	20295
Adjusted R^2	0.902	0.868	0.879	0.831

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 6: Excluding SOEs, Small and Low Rating Firms

This table provides further robustness tests by excluding firms with certain characteristics to alleviate the impact of varying firm composition before and after 2008q4. Column (1) - (2) limits the analysis to non-SOE firms only. In column (3) - (4), we exclude all small firms while in column (5) - (6), we leave only firms with ratings above "B". The regression model in odd columns is the same as that in column (5) in Table 4. The FEs in these columns are all interacted with loan type FEs except for the firm*time FEs, consistent with Table 4. To save space, we run the same regressions as in Table 5 for the three sub-samples and stack the estimated coefficients in odd columns. For example, in column (2), the coefficient for $Unsecured * Post$ corresponds to the coefficient for $Post$ in column (1) of Table 5, only that we exclude all SOE firms here. Other coefficients can be interpreted in a similar way.

	Non-SOEs Only		Large & Medium Firms Only		Rating AAA-B Only	
	Ln(1+LoanVolume)	Volume Share	Ln(1+LoanVolume)	Volume Share	Ln(1+LoanVolume)	LoanShare
	(1)	(2)	(3)	(4)	(5)	(6)
$Unsecured * Post$		-0.008***		-0.009*		-0.007**
		(-3.20)		(-1.86)		(-2.19)
$Collateral * Post$	0.607***	0.041***	0.555***	0.043***	0.555***	0.038***
	(10.52)	(6.11)	(6.39)	(5.47)	(9.41)	(6.00)
$Pledge * Post$	0.135***	0.001	0.087	-0.000	0.083*	0.001
	(3.22)	(0.46)	(1.31)	(-0.05)	(1.85)	(0.22)
$Guarantee * Post$	-0.002	-0.030***	-0.035	-0.030***	-0.016	-0.028***
	(-0.03)	(-4.64)	(-0.38)	(-3.78)	(-0.25)	(-4.52)
Constant	7.901***		-1.808		0.910	
	(6.98)		(-0.42)		(0.78)	
Branch Share Control	✓	✓	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Size FE	✓	✓	✓	✓	✓	✓
Ownership FE	✓	✓	✓	✓	✓	✓
Firm FE		✓		✓		✓
*Firm * Year-quarter FE*	✓		✓		✓	
N	76280		48832		79652	
Adjusted R^2	0.903		0.902		0.905	

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 7: Excluding Government Expenditure Shocks Related Industries

This table provides further robustness tests by excluding firms operating in industries related to government expenditure shocks. We adopt two criterion when determining related industries: (1) Directly affected: transportation, construction, real estate, and infrastructure (column (1) - (2)); (2) Indirectly affected: basic metals and non-metallic mineral production, mining and quarrying (column (3) - (4)). The regression model in column (1) and (3) is the same as that in column (5) in Table 4. The FEs in column (1) and (3) are all interacted with loan type FEs except for the firm*time FEs, consistent with Table 4. To save space, we run the same regressions as in Table 5 for the two sub-samples and stack the estimated coefficients in column (2) and (4), respectively. For example, in column (2), the coefficient for $Unsecured * Post$ corresponds to the coefficient for $Post$ in column (1) of Table 5, only that we exclude all small firms here. Other coefficients can be interpreted in a similar way.

	Criterion #1		Criterion #2	
	Ln(1+LoanVolume) (1)	Volume Share (2)	Ln(1+LoanVolume) (3)	Volume Share (4)
$Unsecured * Post$		-0.007**		-0.006**
		(-2.41)		(-2.22)
$Guarantee * Post$	-0.049	-0.029***	-0.008	-0.027***
	(-0.80)	(-4.62)	(-0.13)	(-4.39)
$Mortgage * Post$	0.550***	0.038***	0.552***	0.037***
	(9.11)	(5.72)	(9.65)	(5.84)
$Pledge * Post$	0.098**	0.002	0.086*	0.001
	(2.13)	(0.71)	(1.94)	(0.20)
Constant	1.265***			
	(3.69)			
Branch Share Control	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Size FE	✓	✓	✓	✓
Ownership FE	✓	✓	✓	✓
Firm FE		✓		✓
*Firm * Year-quarter FE*	✓		✓	
N	73652		80536	
Adjusted R^2	0.899		0.906	

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 8: Heterogeneity Analysis for SOE and Foreign Trading Firms

This table reports the heterogeneity analysis on SOEs and firms operating in foreign trade industry. We define a dummy *Type* which equals to 1 if the firm is a SOE (foreign trading firm), and 0 otherwise in column (1) - (2) ((3) - (4)). We then interact the *Type* dummy with the previous loan type and time dummies and include the triple interaction terms to replicate Table 6.

	Type = SOE		Type = Foreign Trade	
	Ln(1+ LoanVolume) (1)	Volume Share (2)	Ln(1+ LoanVolume) (3)	Volume Share (4)
$Unsecured * Post$		-0.008***		-0.005
		(-3.22)		(-1.62)
$Guaranteed * Post$	0.003	-0.029***	-0.033	-0.028***
	(0.05)	(-4.60)	(-0.52)	(-4.37)
$Mortgage * Post$	0.606***	0.040***	0.548***	0.037***
	(10.47)	(6.10)	(8.93)	(5.69)
$Pledge * Post$	0.132***	0.001	0.374	-0.001
	(3.14)	(0.43)	(1.41)	(-0.45)
$Type * Unsecured * Post$		0.028		-0.032*
		(1.30)		(-1.85)
$Type * Guaranteed * Post$	-0.263	0.015	0.161	-0.003
	(-0.72)	(0.65)	(0.75)	(-0.15)
$Type * Mortgage * Post$	-0.724**	-0.035*	0.065	0.012
	(-2.23)	(-1.87)	(1.50)	(0.52)
$Type * Pledge * Post$	-0.667**	-0.007	0.318	0.033
	(-2.35)	(-0.92)	(1.36)	(1.52)
Constant	1.243		1.065	
	(1.01)		(0.88)	
Branch Share Control	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Size FE	✓	✓	✓	✓
Ownership FE	✓	✓	✓	✓
Firm FE		✓		✓
*Firm * Year-quarter FE*	✓		✓	
N	81180		81180	
Adjusted R^2	0.905		0.905	

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 9: Maturity Shortening

This table reports the changes of maturity post 2008q4. To capture the changes in loan maturity, the analysis in this table is based on loan-level data instead of firm-level outstanding loan volume. The dependent variable is loan maturity in year. *Post* is a dummy variable that equals to 1 if the loan is issued post 2008q4, and 0 otherwise. Column (2) decomposes the *Post* dummy into four interactions terms, each representing one type of bank loan. Control variables include loan volume (in log), bank share controls, industry share controls, rating FEs, size FEs, loan type FEs, and firm FEs.

	Maturity	
	(1)	(2)
$Post$	-0.037**	
	(-2.30)	
$Unsecured * Post$		-0.434**
		(-2.04)
$Guarantee * Post$		-0.020
		(-0.80)
$Mortgage * Post$		0.007
		(0.53)
$Pledge * Post$		-0.099***
		(-4.60)
$Ln(LoanVol)$	0.047***	0.048***
	(7.03)	(7.11)
$Constant$	-0.863*	-0.969**
	(-1.85)	(-2.03)
Branch Share Control	✓	✓
Industry Share Control	✓	✓
Rating FE	✓	✓
Size FE	✓	✓
Loan Type FE	✓	✓
Ownership FE	✓	✓
Firm FE	✓	✓
N	31195	31195
Adjusted R^2	0.759	0.761

*, **, *** stands for significance at 10%, 5%, 1% level, respectively.
T statistics reported in the parentheses below estimated parameters.
Standard errors clustered at firm level.

Table 10: Relationship and Collateral, Substitutes?

This table reports the results that focus on the possible substitution effect between relationship and collateral. Panel A investigates the problem of how pre-existing relationship is related to bank loan volume on average and post 2008. The dependent variable in column (1) -(2) is the total bank loan volume issued to a firm in each year while the dependent variable in column (3) - (6) is a dummy variable that indicates whether the firm received any bank loan in each year. *Rela* is a dummy variable that equals to 1 if the firm has ever borrowed from the bank in any previous year. Similar to *Post* in previous analysis, *Post*08 is a dummy of time. As we use yearly instead of quarterly data here, to align with the definition of *post*, we define *post*08 to be equal to 1/4 in 2008, 1 here after, and 0 otherwise. Column (1) - (4) presents the OLS results. As the dependent variable $1\{Newloan\}$ is a dummy variable, we also try logit and panel logit regressions in column (5) and (6), respectively. We control for industry, rating, size, firm type, year FEs and also firm FEs in odd columns.

Panel A.

	Ln(1+LoanVolume)		1{Newloan}			
			OLS		Logit	
	(1)	(2)	(3)	(4)	(5)	(6)
Rela	0.267***	0.214***	0.542***	0.203***	2.604***	2.772***
	(4.72)	(4.38)	(36.19)	(9.87)	(28.79)	(14.43)
$Rela * Post08$	-0.145*	-0.037	-0.728***	-0.950***	-3.470***	-10.993***
	(-1.85)	(-0.36)	(-39.80)	(-58.32)	(-33.66)	(-13.94)
Constant	6.704***	6.763***	0.513***	0.835***	-2.411***	
	(213.34)	(150.86)	(70.88)	(77.88)	(-4.78)	
Industry FE	✓	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Size FE	✓	✓	✓	✓	✓	✓
Ownership FE	✓	✓	✓	✓	✓	✓
Firm FE		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓
N	5470	4602	9934	9858	9927	6674
Adjusted R^2 *(Pseudo* R^2*)*	0.386	0.850	0.152	0.565	0.119	0.365

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level in column (1) - (5).

Panel B.

Panel B further address the question of whether pre-exitsing relationship could mitigate the rise in collateral requirements post 2008q4. Here we limit the sample to firms that borrowed from the bank for at least once before 2008q4 and label these firms as "old clients". Then we follow the setting in Table 6 and redo the regression.

	Old Clients Only	
	Ln(1+LoanVolume) (1)	Volume Share (2)
$Unsecured * Post$		-0.007**
		(-2.25)
$Guarantee * Post$	-0.014	-0.028***
	(-0.22)	(-4.54)
$Mortgage * Post$	0.556***	0.038***
	(9.40)	(5.96)
$Pledge * Post$	0.089**	0.001
	(1.99)	(0.32)
$Constant$	1.147	
	(0.94)	
Branch Share Control	✓	✓
Industry Share Control	✓	✓
Rating FE	✓	✓
Size FE	✓	✓
Ownership FE	✓	✓
Firm FE		✓
*Firm * Year-quarter FE*	✓	
N	69412	
Adjusted R^2	0.898	

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Table 11: Collateral Constraint and Firm Outcomes

This table presents firm-level analysis on how collateral structure change is associated with firm patent applications and TFP. The dependent variable in column (1) - (3) is the total number of patent applications (in log) and TFP in column (4) - (6). We compute the average change in collateral structure of outstanding bank loans before and after 2008q4 for each firm and define *Posi* as the dummy variable that equals to 1 for firms with increased volume share of mortgage and pledge loans (column (1) - (2)), mortgage loans only (column (3) - (4)), and pledge loans only (column (5) - (6)). Similar as in panel A of Table 9, the dummy *Post*08 equals 1/4 for 2008, 1 for years afterwards, and 0 otherwise. Control variables include firm age (in log), asset (in log), return on asset (ROA), liquidity ratio (LiquidR), HHI (industry Herfindahl-Hirschman index). We include firm and year fixed effects.

	Ln(1+Patents)			TFP		
	Increased Volume Share of:					
	M & P (1)	M (2)	P (3)	M & P (4)	M (5)	P (6)
$Top * Post08$	-0.113*	-0.106*	0.102*	0.003	-0.024	0.094
	(-1.88)	(-1.82)	(1.90)	(0.06)	(-0.44)	(1.07)
$Ln(Age+1)$	0.348***	0.349***	0.354***	0.413***	0.412***	0.414***
	(3.72)	(3.71)	(3.71)	(3.02)	(3.01)	(3.05)
$Ln(Asset)$	-0.051*	-0.052*	-0.057*	0.088	0.088	0.084
	(-1.70)	(-1.73)	(-1.89)	(1.38)	(1.39)	(1.32)
ROA	0.063	0.075	0.078	3.646***	3.645***	3.649***
	(0.34)	(0.41)	(0.43)	(11.64)	(11.65)	(11.72)
$LiquidR$	0.132**	0.137**	0.141**	0.189**	0.189**	0.192**
	(2.03)	(2.10)	(2.14)	(2.22)	(2.21)	(2.24)
HHI	-0.813*	-0.808*	-0.695	0.844	0.816	0.830
	(-1.87)	(-1.86)	(-1.60)	(1.48)	(1.44)	(1.48)
$Constant$	-0.155	-0.150	-0.124	2.159***	2.159***	2.195***
	(-0.50)	(-0.48)	(-0.39)	(2.96)	(2.95)	(3.01)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
N	3705	3705	3705	3044	3044	3044
Adjusted R^2	0.342	0.342	0.341	0.743	0.743	0.743

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.

Appendix

Figure A1: City-level Total Outstanding Bank Loan Volume

This figure shows the total volume of outstanding banks loans in the prefecture city related to our bank loan sample (the gray bars). Data for the total volume of outstanding banks loans at the prefecture city level comes from the CEInet statistics database. The blue line corresponds to the volume of outstanding bank loans covered by our sample as a percentage of total outstanding loan volume in that prefecture city.

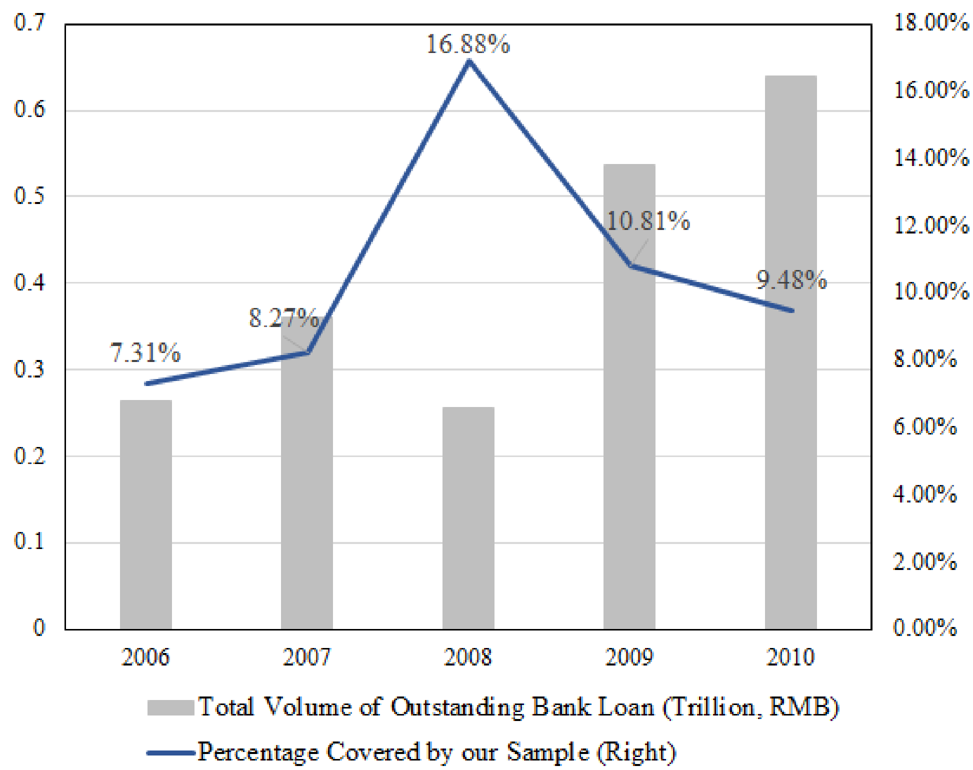


Table A1: Double Cluster at Firm-Quarter Level

This table replicates the baseline findings in Table 4 (panel A) and Table 5 (panel B) but instead double clusters the standard error at firm-quarter level.

Panel A:

	$Ln(1+LoanVol_{i,k,q})$				
	(1)	(2)	(3)	(4)	(5)
Guaranteed ∗ Post	-0.063	-0.063	-0.014	-0.014	-0.014
	(-0.61)	(-0.61)	(-0.22)	(-0.22)	(-0.22)
Mortgage ∗ Post	0.354**	0.354**	0.558***	0.558***	0.558***
	(2.59)	(2.59)	(4.14)	(4.13)	(4.09)
Pledge ∗ Post	0.115	0.115	0.087	0.087	0.087
	(1.64)	(1.64)	(1.47)	(1.47)	(1.45)
Post	0.075*		-0.003		
	(2.04)		(-0.07)		
Constant	2.156***	2.153***	2.288**	2.159**	1.049
	(7.80)	(7.98)	(2.89)	(2.85)	(0.88)
Branch Share Control	✓	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓	✓
*Rating*Loan Type FE*	✓	✓	✓	✓	✓
*Size*Loan Type FE*	✓	✓	✓	✓	✓
*Ownership*Loan Type FE*	✓	✓	✓	✓	✓
Firm FE			✓	✓	
Year-quarter FE		✓		✓	
*Firm * Year-quarter FE*					✓
N	81968	81968	81180	81180	81180
Adjusted R^2	0.393	0.393	0.882	0.883	0.905

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors double clustered at firm-quarter level.

Panel B:

	Fraction of:			
	Unsecured Loan	Guaranteed Loan	Mortgage Loan	Pledge Loan
	(1)	(2)	(3)	(4)
Post	-0.007*	-0.028***	0.038***	0.001
	(-2.03)	(-3.46)	(4.14)	(0.23)
Constant	0.114	0.170	0.716***	0.023
	(1.63)	(1.55)	(4.86)	(0.49)
Branch Share Control	✓	✓	✓	✓
Industry Share Control	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Size FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N	20295	20295	20295	20295
Adjusted R^2	0.902	0.868	0.879	0.831

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors double clustered at firm-quarter level.

Table A2: Interest Rate Analysis

This table focuses on the changes in interest rate. The dependent variable is loan level interest rate (%). *Post* is a dummy variable that equals to 1 if quarter q is post or equal to 2008q4, and 0 otherwise. *Guaranteed*, *Mortgage*, *Pledge* equals to 1 if the loan is a guaranteed, mortgage, pledge loan, respectively, and 0 otherwise. Column (1) - (2) thus analyses the changes in interest rate for different types of loans post 2008q4, as compared to unsecured loans. Column (3) and (4) focuses on the differences in interest rate as distinguished by firm ownership and industry post 2008q4. *Type* equals to 1 if the firm is a SOE (belongs to foreign trade industry), and 0 otherwise in column (3) ((4)). $Ln(Volume)$ stands for the loan size (in log) and *Maturity* is the loan maturity in year. Branch share controls, industry share controls, rating FEs, size FEs, loan type FEs, firm type FEs are included in all models while we also control for firm FEs and year-quarter FEs in column (2) - (4).

	Rate (%)			
			Type = SOE	Type = Foreign Trade
	(1)	(2)	(3)	(4)
Post	-1.628***			
	(-10.18)			
$Type * Post$			-0.825*	0.156*
			(-1.85)	(1.78)
$Guaranteed * Post$	-0.091	-0.024		
	(-0.58)	(-0.13)		
$Mortgage * Post$	-0.062	-0.066		
	(-0.40)	(-0.35)		
$Pledge * Post$	-0.590**	-0.768***		
	(-2.17)	(-2.73)		
$Ln(Volume)$	-0.020	-0.012	-0.009	-0.010
	(-1.42)	(-1.02)	(-0.76)	(-0.79)
Maturity	0.200***	0.268***	0.273***	0.278***
	(8.90)	(7.63)	(6.82)	(7.46)
Constant	5.449***	7.376***	8.883***	7.695***
	(14.61)	(5.06)	(6.23)	(5.31)
Branch Share Controls	✓	✓	✓	✓
Industry Share Controls	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Size FE	✓	✓	✓	✓
Loan Type FE	✓	✓	✓	✓
Ownership FE	✓	✓	✓	✓
Firm FE		✓	✓	✓
Year-Quarter FE		✓	✓	✓
N	28930	28460	28460	28460
Adjusted R^2	0.729	0.901	0.899	0.897

*, **, *** stands for significance at 10%, 5%, 1% level, respectively. T statistics reported in the parentheses below estimated parameters. Standard errors clustered at firm level.