Corporate Default Risk and Loan Pricing Behavior in China

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Abstract

This paper studies banks' loan pricing behavior in mainland China during 2003--2013 by applying panel regressions to firm-level loan data and the estimated default likelihood for listed companies. We find that with the progress of market-oriented financial reforms, banks generally require compensation for their exposure to borrowers' default risks. It is even more so if the borrower is a non-state-owned enterprise (Non-SOE), mainly due to the pricing behavior of the Big Four banks. On the other hand, bank lending rates are less sensitive to the default risks of state-owned enterprises (SOEs). Our results also reveal that banks priced in firm default risks before 2008 financial crisis, but not necessarily so after the crisis. As for industries, we find that after the 2008 Global Financial Crisis, the real estate sector and other government-supported industries tended to enjoy better terms on loan pricing in terms of default risks. We believe the main reason is that the government stimulus policies tilted towards those industries that have played crucial roles in China's economic growth.

Keywords: Default Risk, Bank Loan Pricing, SOE, Non-SOE, China

JEL classification: C13, C23, E43

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1. Introduction

Commercial banks occupy the central role in China's financial market. Although direct financing (i.e., bond issues and equity financing) has been increasing in the last two decades, bank lending remains the major source of financing for most Chinese firms. In 2016, the outstanding bank loans reached RMB107 trillion, which accounted for 82% of direct and indirect financing (i.e., the sum of bank loans, bond financing, and equity financing), or 70% of the aggregate financing (Figure 1), way above the total amount of other financing quantities. Given the importance of loan financing in China, it is natural to ask whether loans are priced in a market-oriented way, thus reflecting borrower's default risks.

Since the late 1990s the market-oriented financial reform has made a significant progress, and commercial bank's risk management skills, including skills in pricing borrower's default risks, have also improved. However, the clients commercial banks deal with are not homogeneous. Some borrowers may have large market power, and some may receive government support more than others, etc. These heterogeneities tend to entangle with firm default risks and thus affect loan pricing. Furthermore, loan pricing could be affected by business cycle. When a market fails, credit does not appear to be priced and distributed normally. Instead, credit rationing may arise with the lending rates being set low to provide relief for distressed firms. During the 2008 Global Financial Crisis, for example, the domestic lending rate fell significantly and remained low for a long period of time (Figure 2).

The primary objective of this study is to investigate whether risk-adjusted loan pricing towards domestic firms is a common practice in China. Specifically, our study focuses on the following aspects: (1) comparing risk pricing for loans to state-owned enterprises (SOEs) with that for loans issued to Non-SOEs; (2) contrasting lender's loan pricing before and after the Global Financial Crisis; (3) conducting an examination of loan pricing for loans to different industries. Such a study is meaningful in the sense that, the capability of a firm's external financing in China is mainly associated with firm ownership. Given that SOEs have a large market influence in many industries, they have greater bargaining power when they borrow from banks. They are also able to obtain better terms on loan contracts because of explicit or implicit government guarantees. In comparison, commercial banks are state-owned as well, and they are expected to participate in government intervention and come to the aid of firms in case of financial distress. Therefore, their loan pricing behavior at normal time might be different from that during a period of financial distress. In short, the study can help us understand the role of firm ownership structure in bank's loan pricing in the different stages of a business cycle. The study can also help us understand the industrial overcapacity problem associated with bank lending after the Global Financial Crisis, although we would not discuss it in detail.

We utilize a proprietary manually-collected loan dataset at firm level combined with firm default likelihood series to explore the issues. We find that banks generally charge higher lending rates for higher firm default risks. However, the sensitivities of bank lending rates to the default risks of different types of firms are quite different. Banks seem to be less sensitive to SOEs' default risks than to those of Non-SOEs, due to their different ownership structures. Furthermore, evidence has shown that the bank lending pattern after the financial crisis differs from that before the financial crisis. Banks tended to ignore firm default risks in their loan pricing after the financial crisis, and the Big Four banks had a stronger obligation to come to the aid of SOEs than other banks during that period. Finally, our study reveals that, despite the fact that the government-supported industries, including the real estate sector, were not treated differently from other industries before the Global Financial Crisis, they obtained better terms on loan pricing after the crisis. To come to the point, the firm ownership and the business cycle to certain extent distorted banks' pricing behaviors towards firm default risks.

The remainder of this paper is organized as follows: Section 2 reviews the prior research. Section 3 lays out the research framework along with the data description. The empirical results are reported in Section 4, followed by robustness check in Section 5. Section 6 concludes the paper.

2. Related Literature

Commercial loans are important in the conduct of business operations in modern society. Firms utilize commercial loans to finance their short-term liquidity needs and long-run investments. Theoretically, in a competitive risk-free market, the commercial loan price is determined by the risk-free rate and the marginal cost of intermediation, whereas in an imperfect market with uncertainty, loan pricing is in addition affected by many other factors, such as firm default risk, firm information risk, monetary policy, etc. Firm default risk is a major lending risk faced by banks and is one of the primary determinants of loan pricing. The relationship between the commercial lending rate and firm default risk is described in the Monti-Klein model (Freixas and Rochet (2008)). While the Monti-Klein model considers borrowing activities in a closed economy, studies like those of Agenor et al. (2008) and Neumeyer and Perri (2005) model loan pricing in terms of default risks in an international capital market environment. Empirical evidence reveals that banks structure their loan contracts to reflect their risk exposure. For example, Blackwell and Winters (1997) classify medium and low risk borrowers based on commercial banks' monitoring frequency and find that medium-risk borrowers need to pay a significantly higher loan rate than low-risk borrowers. Strahan (1999) and Bharath et al. (2008) use bank loan data from the Dealscan database provided by Loan Pricing Corporation to investigate the influence of a borrower's accounting quality in loan contract terms. They find that poorer firm accounting quality, which reflects firms' high default risks, was significantly associated with higher loan interest rate for the period 1998--2003 in the US. Machauer and Weber (1998) use data from five major German banks to study the relation between debt contracting and borrower's risk assessed by banks' internal credit rating systems and find similar loan pricing patterns.

The information risk is another crucial component in bank loan contracting in addition to credit risks (Bhoraj and Sengupta (2003)). Information disclosure and alleviated information asymmetry are associated with increased loan origination (Jappelli and Pagano (1993); Dennis and Mullineaux (2000)) or with reduced cost of capital (Easley and O'Hara (2004)). Measures to reduce information asymmetry or incompleteness, such as borrower-lender relationship or good corporate (country) governance, therefore, play a significant role in loan contracting. Theoretically, a borrower can benefit from such a relationship due to bilateral information sharing, reduced monitoring costs, and easier debt renegotiation (e.g., Bhattacharya and Chiesa (1995); Berlin and Mester (1992); Boot et al. (1993); Rajan and Winton (1995)). Empirical studies (e.g., Bharath et al. (2009); Peterson and Rajan (1994); Berger and Udell (1995); Cole (1998); Degryse and Van Cayselee (2000); Smith (2003); Peek and Rosengren (2002)) largely support the theoretical view that firms who have a strong affiliation with banks can more easily obtain preferential loan terms than those with weak affiliations. Theoretical and empirical studies also demonstrate that good corporate or country governance can discipline managers' behavior and reduce firms' information opaqueness, leading to higher chance of loan approval or lower borrowing rate (Bae and Goyal (2009); Francis, et al. (2012)).

Aside from firm default risk and information risk, monetary policies affect loan pricing as well, because a policy not only affects the benchmark rate, but may also change the risk appetite of both creditors and borrowers. The same is true during or after a financial crisis when a monetary policy is rolled out to mitigate output drops and stabilize the financial market. As such, the abundant liquidity and low policy rate may spur banks' risk taking, leading to credit flowing to risky borrowers with low lending rates. For instance, Aramonte et al. (2015) investigate risk taking in the U.S. syndicated loan market during the period of low interest rate after the Global Financial Crisis. They find that many non-bank lenders invested in riskier loans during the period. Aside from the U.S. market, Jimenez et al. (2014) investigate Spain's credit market, and find that a low overnight rate could induce large loans to risky firms even without sufficient collateral. Ioannidou et al. (2015) report similar findings in Bolivia's credit market.

The empirical literature discussing the relationship between loan contracting and firm characteristics in China has grown in recent years. For example, Sun and Liu (2011) report that loan allocation is significantly associated with firm financial-related characteristics and agency cost. Apart from the financially related ones, another important firm characteristic in addition to financial related ones in an emerging market is firm ownership. Sun and Liu (2011) reveal that banks do not seem to differentiate between SOEs and Non-SOEs in decision making for loans. However, Sun et al. (2006) prove that, while a firm's earning performance is an important factor in loan origination, its importance declines when the loan applicant is a SOE. The reason behind this is the implicit government guarantee for SOEs.[1] Cull and Xu (2003) report a positive correlation between SOE profitability and bank financing in the 1980s, but that the correlation weakened in the 1990s, which may reflect banks' responsibilities of bailing out indebted SOEs. Li et al. (2009) utilize a firm-level dataset from the National Bureau of Statistics (NBS) to examine the effect of institutional

[1] In general, politically connected firms can borrow more with higher ex post default rates (Khwaja and Mian (2005)) or with lower rates (Sapienza (2004)).

development and ownership structure on the loan contract terms of Chinese manufacturing firms. They demonstrate that, compared with Non-SOEs, SOEs have better access to long-term debt and thus enjoy more leverage.

Our study follows the theoretical framework of Freixas and Rochet (2008), complementing the existing literature along several dimensions. First, we study banks' loan pricing behavior in China by using contract-specific data, which is unique in China's bank lending literature. Contrary to our work, studies by Sun and Li (2011), Sun et al. (2006), Cull and Xu (2003), and Li et al. (2009) are primarily about determination of loan quantity, and the data they employ are aggregate bank lending data or firm accounting information. Second, we estimate firm default risks using the maximum likelihood method under the Black-Scholes-Merton structural model, whereas other studies on bank lending behavior in China generally use accounting indicators as risk measures. Third, we study banks' loan pricing behavior not only from the demand side (i.e., in terms of firm ownership, and industries), but also from the supply side (i.e., in terms of bank types). Fourth, we investigate bank's loan pricing behavior in different stages of a business cycle, taking into consideration the monetary policy stance. Our study is beneficial in assessing China's bank lending behavior and may shed light on its macro prudential practices in the future.

3. Research Framework and Data

3.1. Empirical Framework

Our empirical model follows the theoretical framework described in Freixas and Rochet (2008). Basically, the lending rate is determined by the benchmark interest rate adjusted for loan term, loan size, and borrower's default risk *DLI*. In addition, we add firm characteristics and a macro indicator as control variables, and the empirical model is expressed as:

$$Lrate_{it} = \beta_0 + \beta_1 DLI_{it-1} + \beta_2 Lsize_{it} + \beta_3 Brate_{t-1} + \beta_4 Lterm_{it} + \gamma X + \varepsilon_{it} \qquad (1)$$

where the dependent variable, $Lrate_{it}$, is the interest rate for loan i issued at time t. Among the explanatory variables, β_0 is a constant, DLI_{it-1} is the default likelihood at time t-1 for the firm who receives loan *i* at time *t* with amount of $Lsize_{it}$ and maturity of $Lterm_{it}$, $Brate_{t-1}$ is the benchmark interest rate prevailing at time *t-1*, and *X* is the vector of the control variables, including macro indicators and firm characteristics that will be described later.

Prior empirical work, as reviewed by Dennis et al. (2000), has concludes that certain firm characteristics affect loan contracting. Accordingly, we add firm tangible assets, the market-to-book ratio, firm leverage ratio, and firm profitability as control variables. We also include the required reserve ratio as a macro control (which also partly reflects monetary policy stance). Our focus is the coefficient to DLI_{it-1}, β_1, which is expected to be both positive and significant, if banks require a premium for firm default risks.

Panel regressions are applied to quarterly data to estimate the empirical model. All explanatory variables, except loan features, are lagged one quarter to avoid the endogeneity problem. Autocorrelations, year effect and heteroscedasticity in industries, bank types, and locations of bank headquarters are controlled for in the regressions.

3.2. Data

The study is for listed companies only. Quarterly data ranging from 2003Q2 to 2013Q2 are used in the regressions. They consist of three parts: (a) firm default likelihood, (b) firm loan features, and (c) macro indicators and firm characteristics.

(a) Firm default likelihood (*DLI*)

Default risks may be gauged by pre-existing default history or ex-post loan default rates (see for example, Jimenez et al. (2014); and Ioanniedou (2015)), or by default probability, which is an expectation on firm default in the future. Default probability can be estimated by reduced-form or structural models. The reduced form models are heavily reliant on historical accounting or macro information (see for example, Altman (1968); Ohlson (1980); Shumway (2001); Hillegeist at al. (2004); Campbell at al. (2008); Altman at al. (2011); and Duan at al. (2012)). In comparison, the structural models contain both historical accounting information and forward-looking market price information and are thus regarded as better tools for default prediction when the market is relatively efficient or well developed (McQuown (1993)).

We adopt firm default prediction obtained from a structural model as a measure of firm default risk, with the risk neutral probability estimate being called default likelihood (Altman et al. (2011)). Basically, we apply the maximum likelihood method proposed by Duan (1994) to estimate firm distance to default and, hence, default likelihood under the Black-Scholes-Merton option pricing framework, where a firm's market value of equity and value of debt are the inputs for estimation (see Appendix for details).[2] The original data series used to construct quarterly equity value of equity and value of debt are available in Bloomberg. The average *DLI* is 0.15 with a variation of 0.21.

(b) Loan features

Loan information for individual firms, including loan size (*Lsize,* in logs), lending rate (*Lrate*), and loan term (*Lterm*), is manually collected from firm financial statements in WIND.[3] Much more loan information is available after 2007 than before, as the Chinese Securities Regulatory Commission (CSRC) enacted more stringent regulations to require listed enterprises to disclose any important financial condition changes in the early part of 2007.

However, not all loans to the listed firms are reported, as the CSRC only requires information about those that might have important influences on firm stock price. In addition, some key information is missing in some listed firms' loan disclosures. For example, firms only report the loan size and bank name but not their borrowing costs. Hence, we remove loan records without information about interest rates or loan maturities. To avoid exchange rate expectation problems, we also eliminate loans that are issued in foreign currencies. The final sample contains 12039 loans to 665 listed firms.

We observe that the loan interest rates in the sample range from a minimum of zero to a high of 26.1%, with a mean of 6.3% and standard deviation of 1.4%.[4] The loan maturity ranges

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[2] The default likelihood *DLI* was applied to study credit risk spillovers in Chan et al. (2016) and Han and Zheng (2016).
[3] The dataset was used to study monetary transmission mechanism by He and Wang (2013).
[4] Zero rates are often offered to firms in old revolutionary base, minority-inhabited, border, and poverty-stricken areas.

from the minimum of 2 months to the maximum of 30 years, with the mean of 3.9 years, indicating that a substantial fraction of loans is not for working capital needs. The mean of the loan amount in logs is 17.6 (or RMB44 million in original value) with the minimum amount of 8.0 (or RMB3000 in original value) and the maximum of 22.86 (or RMB8.5 billion in original value).

(c) Macro indicators and firm characteristics.

The macro indicators include the benchmark interest rate (*Brate*) and the required reserve ratio (*RRR*). In Freixas and Rochet (2008), the benchmark rate is the inter-bank market rate, whereas in the current study *Brate* is the 1-year benchmark lending rate, which is available in CEIC. *Brate* has a mean of 6.23% with a standard deviation of 0.77%. *RRR* is also available in CEIC, and ranges from 6% to 21%.

Firm characteristic variables, such as tangible assets (*Tangble*), the market-to-book ratio (*MTB*), and leverage (*Lev*) are constructed based on firm financial statements.[5] *Tangble* has a mean of 0.60 ranging from 0.07 to 1.0, whereas the mean of *MTB* is 1 with a narrower range from 0.86 to 1.08, indicating that firm market value is close to its book value. The mean of *Lev* is 1.58 with a standard deviation of 0.33.

Statistics for variables are summarized in Table 1. Table 2 lists variable correlations. Some variables have relatively high correlations. For example, correlations between *Brate* and *Lterm*, between *Lsize* and *Lterm*, and between *Tangble* and *MTB* seem to be relatively high, which may affect the estimated value of coefficients to these variables. However, their impact on the estimated value of the coefficient to *DLI* should be small, as *DLI* has relatively low correlations with other variables, except with *Lev*.

4. Empirical Results

[5] Here *Tangble* = (0.715*receivables + 0.547*inventory + 0.535* net fixed assets + cash)/book value of assets, *Lev* = 1+ln(book value of assets/total liabilities). According to these definitions, higher *Lev* means lower leverage ratio. See Zhang et al. (2015) for details.

In this section, we report our main results concerning the effect of corporate default risk on banks' loan pricing behavior. We also present several sub-sample regressions to investigate banks' pricing logics in China.

4.1. Benchmark Regressions

We begin the analysis by studying whether banks in general require a higher loan rate for compensation if they are exposed to a more severe default risk without distinguishing firm ownership, bank types, and the business cycle.

The regression results are reported in Table 3.[6] In general, the default risk is taken into consideration in banks' loan pricing. In RegA1, loans are priced in terms of corporate default risk, loan size, and the benchmark rate adjusted for loan term, as described in the typical banking theory with imperfect capital market. The estimated coefficient to default likelihood is significant at the 5% level, suggesting that banks require a higher loan rate for compensation when they are exposed to a more severe default risk. When a firm's default likelihood increases by 1%, the lending rate tends to increase by 0.15%.

Consistent with findings in the literature, the coefficient to loan size, which is equivalent to the inverse of the price elasticity of loan demand in the Monti-Klein model, and also captures economies of scale in bank lending, is negative and significant, suggesting that larger loans are associated with lower lending rates. The coefficient to the benchmark rate is positive and significant, confirming that the actual lending rate is guided by the benchmark rate. We control for the loan term because the lender may require a term premium for longer-term debts, and this term premium translates into a higher loan interest rate. Although insignificant, the coefficient to loan term is positive, indicating that banks generally charge more for longer-term loans.[7]

The RegA2 in Table 3 includes the required reserve ratio as a macro control variable. The regression shows that the signs of the coefficients to the existing independent variables are

[6] Estimate for the constant term β_0 is suppressed in all of our regression reports.

[7] In some cases, lenders may provide price discount for longer-term high quality loans, thus term premium can be negative. We will discuss this later.

retained; it also shows that the higher *RRR*, which is an indicator of tighter liquidity and monetary policy, leads to a higher lending rate.

We further add firm characteristics as control variables, and the result is shown in RegA3. Again, the coefficient estimators in RegA1 and RegA2 are robust to the inclusion of firm characteristics (which also leads to the significant estimator for the coefficient to *Lterm*). The first firm characteristic variable is *Tangble*. Firms with higher tangible assets are usually associated with more collaterals; thus they are likely to have better terms from banks. The second firm characteristic variable, *MTB*, captures firm growth potential. According to Q-theory, a firm with *MTB* greater than unity is undervalued, and is desirable for investment. Therefore, a higher *MTB* tends to be associated with a lower borrowing rate. The regression shows that the coefficient to *MTB* is significantly negative, which is consistent with the theory. The third firm characteristic variable is *Lev*, or the inverse of the leverage ratio. The coefficient to *Lev* is negative and significant, implying that higher leverage ratios are usually associated with higher default risks.

4.2. Firm Ownership, Business Cycle, and Loan Pricing

A potential advantage of SOEs borrowing from banks is that they are explicitly or implicitly guaranteed by the Chinese government, because SOEs have been playing a key role in China's economic growth and social stability. A government guarantee basically means SOEs are hard to fail. When a SOE as a borrower is not able to repay its debts, either the government would directly inject funds to the firm, or the banks are allowed to write off or to make special arrangements for the debts (e.g., debt-to-equity swap) without affecting the evaluation of their performance. The banks are allowed to do so in that, both banks and firms are state-owned, and the relationship between SOEs and banks is more than just being borrowers and lenders. The common background of being controlled by the government, they share the benefits as well as the risk of lending activities, resulting in easier and more flexible loan covenants. In this regard, banks may be less sensitive to the changes in SOEs' default risks compared with those in the Non-SOEs' default risks.

We define a firm as a SOE if the government share accounts for more than 20 percent; otherwise, it is a Non-SOE. According to this classification, around 3200 loans are made for

SOEs and around 7800 loans for Non-SOEs. Banks' loan pricing behavior towards SOEs and Non-SOEs is presented in Table 4.[8]

The regressions of RegB1 and RegB2 in Table 4 are for SOEs. Indeed, the default risk is not taken into consideration by banks when they lend to SOEs, witnessed by insignificant estimators for coefficient to *DLI*. Furthermore, the negative sign of the coefficient to *DLI* in RegB2 tends to support the view of risk-sharing between borrowers and creditors. Contrarily, the estimated coefficients to *DLI* for Non-SOEs are positive and statistically significant at the 5% level in both RegB3 and RegB4, thereby indicating that lenders require a higher interest rate for compensation for larger default risks of Non-SOEs. These results imply that the significant coefficient estimator for default likelihood in the benchmark regressions mainly reflects banks' concern on default risks of Non-SOEs in loan origination.

Aside from the coefficient estimators for *DLI*, estimators for other independent variables are largely in line with that recorded in the benchmark regression. However, several points are worth noting here. First, the term premium for SOEs is less significant than that for Non-SOEs. Second, the coefficients to *Lsize* in RegB3 and RegB4 and the coefficient to *Tangble* in RegB4 are insignificant but with correct signs, which could be caused by loan policy changes after the Global Financial Crisis, and we will check this later. Third, the coefficient to *MTB* in RegB2 seems mysterious, as it means that banks tend to charge higher rates for SOEs with higher *MTB*. One hypothesis is that, growing firms could be vulnerable to financial distress, which may lead to higher borrowing costs. But there is little evidence that SOEs are more vulnerable to the financial distress than Non-SOEs. Another explanation is the profit-sharing between SOEs and banks. As mentioned at the beginning of this section, both banks and SOEs are state-owned, and such common background makes them to share the benefits as well as the risk of lending activities. The positive (and significant) sign of the coefficient to *MTB* could well reflect the benefit sharing among banks and growing SOEs, whereas the coefficient to *DLI* is more likely to reflect their risk sharing behaviors.

[8] According to the National Bureau of Statistics (NBS), loans to SOEs account for 58% of the total loans to firms in 2015, whereas in 2010 the share of loans to SOEs is as high as 62%, where SOEs refer to "state and collective controlled" firms.

As our data sample covers the period of Global Financial Crisis, it is worth investigating whether banks' loan pricing behavior changed after the financial crisis broke out in 2008Q2 and whether the change was related to firm ownership. We divide our sample into two sub-samples and run regressions separately. The results are reported in Table 5, where RegC1 and RegC2 are the regressions for the period before 2008Q2 and after 2008Q1, respectively. As shown in the table, banks took borrowers' default risk into consideration before the crisis. However, default risks appeared to be ignored when banks lend to firms from 2008Q2 to 2013Q2. This finding suggests that after the crisis erupted, banks relaxed lending standards for firms in order to avoid a credit crunch, which is also in line with government-supported policies launched then.

RegC3 and RegC4 in Table 5 are for SOEs, while RegC5 and RegC6 are for Non-SOEs, before 2008Q2 and after 2008Q1, respectively. The coefficient to default likelihood in both RegC3 and RegC4 is insignificant, suggesting that banks ignored SOEs' default risks consistently before and after the crisis. As mentioned earlier, the negative sign of the coefficient to *DLI* in RegC4 may reflect risk-sharing between banks and SOEs. Contrarily, as shown in RegC5 and RegC6, banks were concerned with Non-SOEs' default risks before 2008Q2, but not after 2008Q1, which is a little bit puzzling. Although banks provided liquidity to the market in order to avoid a credit crunch after the Global Financial Crisis, the coefficient to *DLI* for Non-SOEs is expected to be not only smaller than that before the crisis, but also significant due to its ownership. The insignificant estimator for the coefficient to *DLI* in RegC6 thus implies that even under-performing Non-SOEs might have obtained reliefs from government and financial institutions.[9]

Table 5 indicates that the default risk premium charged to Non-SOEs before the Global Financial Crisis is the main reason to the significant coefficient estimator for *DLI* in RegC1. And it is also the main reason to the significant impact of default risks on loan pricing in RegA3 of Table 3, and for Non-SOEs in RegB4 of Table 4. Similarly, the insignificant coefficient estimator for *Lsize* in RegB3 and RegB4 is contributable to that for *Lsize* after the

[9] It is justifiable that many Non-SOEs with good performance are able to obtain loans with preferential terms similar to SOEs after 2008Q1, since Non-SOEs have also contributed greatly to economic growth and social stability. According to the NBS, employment in private firms, foreign-funded firms and Macau-Taiwan-Hong Kong-funded firms (which belong to Non-SOEs) reach 36% of the total urban employment in 2016, compared to 29% in 2013 and 13% in 2003.

Global Financial Crisis in RegC6. Despite the high correlation between *Lsize* and *Lterm*, it is more likely that the insignificant coefficient estimator for *Lsize* for Non-SOEs is caused by the credit crunch faced by Non-SOEs, in which case loan demand is insensitive to the price charged. In comparison, the insignificant coefficient estimator for *Brate* in RegC5 is mainly caused by the high correlation between *Brate* and *Lterm*.[10] For the negative coefficient estimator for *Lterm* in RegC3, a feasible explanation is that, many longer-term loans are treated as high-quality assets, which leads to lower price.[11] Finally, the positive sign of the coefficient estimators to *Lev* and *MTB* in RegC3, though insignificant, could partly reflect the profit sharing between banks and firms just as *MTB* does, which we need further evidence to verify.[12]

4.3. Big Four Banks versus Other Banks

The banking system in China consists of four big state-owned banks (Big Four) plus many small banks, where the Big Four are Industrial and Commercial Bank of China (ICB), Agricultural Bank of China (ABC), Bank of China (BOC), and China Construction Bank (CCB).[13] During the time of financial distress, bank regulation and supervision policies in China require the Big Four to provide significant loans to troubled borrowers, especially to SOEs. Requirements for other banks are not as stringent as for the Big Four, and they have more freedom to pursue their self-interest when making loan decisions. Thus, we make the conjecture that the loan pricing behavior of the Big Four is different from that of other banks. We examine this conjecture and report the results in Table 6.

In RegD1 of Table 6, only the observations for loans by the Big Four to SOEs are included. Again, the focus is default risks. The estimated coefficient to *DLI* is positive but insignificant, indicating that the Big Four do not require a credit risk premium from SOEs. RegD2 is about

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[10] The insignificant coefficient estimator remains when *Lsize* is the only independent variable in the regression for Non-SOEs after the crisis, so does the significantly negative coefficient estimator when *Lterm* is the only regressor for SOEs before the crisis. However, when *Lterm* is dropped out, the coefficient to *Brate* becomes significant in RegC5.

[11] There is evidence that, long-term fixed asset investments, projects supported by the government, or whose products are competitive in the market could be financed by loans with lower rates.

[12] The relatively high correlation between *Lev* and *DLI* could be another reason for the positive sign of the coefficient to *Lev*

[13] According to the CBRC annual reports and individual bank's financial statements, loans issued by the Big Four and Big Four's assets account for 56% and 53% of the total commercial loans and commercial bank assets, respectively, in 2013. The shares are 52% and 46% respectively in 2016.

the lending of the Big Four to Non-SOEs, where the estimated coefficient to *DLI* is positive and significant. This result reveals that the Big Four treat Non-SOEs differently from SOEs, so the default risk of Non-SOEs is under more scrutiny than that of SOEs.

We show in RegD3 and RegD4 loan pricing behaviors by the Big Four for SOEs before and after the Global Financial Crisis. The Big Four priced in SOEs' default risks before the crisis, but tended to ignore the risks after the crisis when stimulus policies were launched. The pricing behavior after the crisis outweighs that before the crisis, which leads to the overall insignificant coefficient estimator for *DLI* in RegD1.

The results are opposite for Non-SOEs. RegD5 shows the Big Four did not price in Non-SOEs' default risks before the crisis. It is probably due to the selection bias, or the Big Four tended to lend to Non-SOEs with good performances. RegD6 demonstrates that after the crisis, the Big Four were concerned with Non-SOEs' default risks, probably because there was no guarantee for Non-SOEs' repayments in an increasing uncertainty environment.[14] The pricing behavior after the crisis leads to the overall significant coefficient estimator for *DLI* in RegD2.[15]

Table 7 reports regression results for other banks' pricing behavior, where RegE1 and RegE2 are for loans to SOEs and Non-SOEs with the whole sample. It appears that other banks do not consider firm default risks when they lend to either SOEs or Non-SOEs. Sub-sample regressions RegE3-RegE6 reveal that other banks only considered Non-SOEs' default risks before the Global Financial Crisis, and the risk premium for Non-SOEs is negative after the crisis (though insignificant). While it is reasonable to ignore the default risk of firms with good performance, it is interesting to see the difference in pricing strategy towards Non-SOEs between the Big Four and other banks after the Global Financial Crisis broke out in 2008 (by comparing RegD6 with RegE6). The aggressive expansion in loans to Non-SOEs made by other banks could partly explain this. As shown in Figure 3, the share of loans to SOEs in other banks' total loans was systematically lower than that in the Big Four's total

[14] One evidence that the Big Four are concerned with Non-SOEs' default risks more than those of SOEs after the crisis is that the changing size of loans they made to different types of firms. Based on our sample, the average size of loans to SOEs made by the Big Four is around RMB100 million after the crisis, twice that for Non-SOEs. However, the loan size for SOEs is 1.3 times that for Non-SOEs before the crisis.

[15] Since most of which have been discussed earlier, we do not examine other coefficient estimators here..

loans after 2008, suggesting that other banks were expanding their client base strategically in the pool of Non-SOEs during the period. Perhaps moral hazard should also be counted besides stimulus policies for other banks' pricing behavior. We will come back to the point later.[16]

4.4. Loan Pricing across Industries

The real estate sector has been expanding rapidly in the last two decades, thereby large capital inflows from the market.[17] Apart from this, many other sectors play a crucial role in promoting employment and maintaining social stability. These industries were strongly supported by the government during and after the Global Financial Crisis. In this section, we aim to investigate whether loan pricing depends on industries, i.e., to test (1) whether the real estate sector obtains better terms on loan pricing, and (2) whether government-supported industries including the real estate sector were treated differently before and after the Global Financial Crisis when they borrow from banks. To be concise, we do not discuss coefficient estimators for control variables.

4.4.1. Loan pricing for the real estate sector

Table 8 reports the regression results for the real estate sector, where *DLI_RET* is the interactive term between the default likelihood and the dummy for the real estate sector. As shown in RegF1 with the whole sample, the coefficient to *DLI* is significantly positive, but the interactive term *DLI_RET* is significantly negative, suggesting that the real estate firms obtain better terms on loan pricing, or banks requires less compensation for their default risks than that for other industries.[18]

Further examining RegF2 and RegF3 reveals that, the real estate firms obtained better terms on loan pricing only after the Global Financial Crisis. While the coefficient to *DLI_RET* in

[16] We find (though not report here) that, before the Global Financial Crisis, other banks tend to price in the default risks of both SOEs and Non-SOEs. However, after the crisis when the Big Four price in the default risks of Non-SOEs, other banks provide better terms to Non-SOEs in terms of default risks.
[17] According to the CBRC and NBS, aside from direct financing from the market, the total real estate loans account for around 20% of the total loans each year from 2010--2015. In 2016, the share of loans to the real estate sector increases to 24%.
[18] The total effect of default likelihood on loan pricing for the real estate sector is 0.16 = 0.235 - 0.495*0.154, giving the mean of the dummy for the real estate industry at 0.154.

RegF3 is -0.6 and significant at the 1% level, it is insignificant in RegF2, indicating that banks did not treat the real estate sector differently from other sectors or industries in terms of default risks before 2008Q2.

4.4.2. Loan pricing for government-supported industries

After the Global Financial Crisis broke out in 2008, the Chinese government launched a series of stimulus measures to stabilize the economy, including encouraging banks to provide loans to distressed companies. To be explicit about its intention, the government publicly announced the industries that would be a focus of its support.[19] Based on its announcement, we group the firms into the government-supported industries and other industries, and find that the government-supported industries continued to obtain large amount of loans after the crisis (Figure 4). Here we investigate whether banks price loans differently for firms in different industrial groups in terms of default risks.

Table 9 contains the regression results for the two groups, where “G-Support” denotes industries supported by the government as announced, and “Others” denotes other industries. We find that the estimated coefficient to *DLI* in RegG1 is negative and insignificant, suggesting that the loan price is insensitive to default risks of firms in the government-supported industries. However, banks did price in the default risk of firms in these industries before the crisis, as shown in RegG2. However, after the financial crisis, the default risks of these firms were ignored due to government support, as witnessed by the insignificant coefficient to *DLI* in RegG3.

For a comparison, regressions RegG4 to RegG6 show how banks price firm default risks in other industries. It appears that banks charged more risk premium for firms in other industries than that in government-supported industries before the financial crisis. The difference is

[19] According to news media and based on the industry classification code provided by the China Securities Regulatory Commission (CSRC), the industries with government support include the following: General equipment manufacturing (Code: 34), Special equipment manufacturing (Code: 35), Automotive manufacturing (Code: 36), Railways, ships, aerospace and other transportation equipment manufacturing (Code: 37), Electricity, heat production and supply (Code: 44), Gas production and supply (Code: 45), Water production and supply (Code: 46), Civil engineering construction (Code: 48), Construction and installation industry (Code: 49), Building decoration and other construction (Code: 50), Rail transport industry (Code: 53), Road transport industry (Code: 54), Water transport industry (Code: 55), Air transport industry (Code: 56), Loading and unloading and transport agency industry (Code: 58), Warehousing industry (Code: 59), and Real estate (Code: 70).

much more significant after the financial crisis broke out, as banks continued to price in default risks of firms in other industries. However, the magnitude of the risk premium for firms in other industries declined after the financial crisis compared with that before the crisis, indicating that these firms more or less benefited from the government stimulus polices.

5. Robustness Check

In the above analysis, we use 20% as a cutoff for firm ownership classification. This cutoff is close to the share holdings by majority shareholders in reality. Another reason to do so is to balance the number of observations between SOEs and Non-SOEs (i.e., to increase observations for SOEs). If we use a cutoff of 50%, then the number of observations for SOEs would be reduced to less than 2400 and that for Non-SOEs would rise to more than 8500. Nevertheless, the findings in the previous sections are robust to a cutoff of 50% (see Tables 10-13).[20] In addition, we use industry classification by the CBRC for our analysis in Section 4.4.2. As a robust check, we also adopt the industry classification provided by the NBS, and group firms into government-supported and other industries accordingly. The findings on banks' pricing behavior in terms of firm default risks remain unchanged when we adopt this industry classification. However, we do not report the results here.

Regarding the unbalanced observation size between SOEs and Non-SOEs, and before and after the Global Financial Crisis, we apply the bootstrap method for a robustness check. It appears that the number of observations for Non-SOEs is much larger than that for SOEs, and the number of observations after the Global Financial Crisis is much larger than that before the crisis. As such, we randomly draw sub-samples with replacement from a bigger dataset for 30 times, with the size of each subsample close to that of its smaller counterparty. We then run regressions based on each subsample, and check how many regressions out of 30 that result in the coefficient estimator for *DLI* consistent with the initial one (i.e., with the same sign and comparable significance). The results are recorded in Table 14. It shows that

[20] As shown in Table 11, the estimated coefficient to *DLI* for SOEs before the Global Financial Crisis becomes significant, but the magnitude of the risk premium for SOEs is still less than that for Non-SOEs. In Table 12, the sign of the estimated coefficient to *DLI* for Non-SOEs before the crisis becomes negative, but still remains insignificant. In Table 13, the estimated coefficient to *DLI* for SOEs becomes significant, which weakens our previous findings slightly.

after resampling, the new results are largely consistent with the initial results. However, the result in RegD6 for Non-SOEs after the Global Financial Crisis becomes less robust, which leads to less robust credit risk premium in RegD2. Similarly, the credit risk premium for Non-SOEs in RegB4 and for firms in other industries in RegG6 becomes less robust, which means Non-SOEs and firms in other industries might obtain better loan term in terms of credit risks.

One concern about the empirical results is the endogeneity of control variables, especially loan size and loan term. Logically speaking, a firm default risk affects its borrowing rate, which would in turn affect its loan demand and loan term. In reality, loans with long maturities are largely project-based, which means loan term and loan size are not always endogenous to firm default risks. In addition, as shown in Table 2, the correlations between default likelihood (*DLI*) and other control variables are not very high, which could, to a certain extent, justify our relatively simple empirical approach. Nevertheless, the endogeneity of the two variables cannot be completely ruled out, and one way to deal with this is to adopt the VAR approach. Alternatively, we run regressions with both loan size and loan term being excluded from the model, because our interest is the coefficient to firm default risk (even though we would slightly deviate from the theoretical framework as described in Freixas and Rochet (2008)). It turns out that most results reported in Section 4 still hold. For example, the coefficient estimators for *DLI* and the benchmark rate are robust on benchmark regressions (in Table 3), on pricing of loans to SOEs and Non-SOEs (in Table 4), on loan pricing before and after the financial crisis (in Table 5), and on loan pricing for the real estate sector (in Table 8). Meanwhile, the coefficient to *DLI* for SOEs in RegD1 of Table 6 becomes negative, but remains insignificant, which is because the coefficient estimator for *DLI* in RegD3 becomes insignificant. The coefficient to *DLI* for NON-SOEs in RegD2 remains positive, but becomes insignificant, due to the insignificance of the coefficient estimator in RegD5. The results in RegD4 and RegD6 still hold. Overall, the coefficient estimators for *DLI* in Table 6 slightly improve our previous findings. In Table 7, the sign and significance of the coefficient estimators for *DLI* and the benchmark rate are almost intact, except the sign of the estimated coefficient to the benchmark rate becomes positive in RegE5, which actually improves our initial result. In Table 9, the estimated coefficient to the benchmark rate in RegG5 and that to *DLI* in RegG6 become insignificant, which slightly weaken our initial results.[21]

Another concern about the empirical results is sample bias. Our sample only covers listed companies, but such companies account for a small portion of nonfinancial firms. It is likely that non-listed firms are more finally constrained, and lending to these firms would be under a closer scrutiny by banks, even after the financial crisis. Therefore, our findings hold for listed companies at most. Furthermore, not all listed firms have disclosed their loan information in their financial statements. As such, the loan information in our datasets is incomplete even for listed firms. The gap between the distribution of loan price in the sample and that of the population recorded by the People's Bank of China during 2008Q1--2011Q4 is summarized in He and Wang (2013). It appears that the share of loans priced at a discount in the sample is larger than that in population, suggesting that the lending rate could be more sensitive to firm default risks if the distribution of loan price in the sample is closer to that in population. We could cross check our results when a more complete dataset is available in the future.

As for results for the sub-sample after the Global Financial Crisis, it should be mentioned that, the loosening in loan pricing in terms of default risks does not necessarily mean that banks generally have a bad practice in risk management. The sample after the financial crisis is up to 2013Q2 when most of the government stimulus measures are still in effect. Thus, banks' insensitiveness to firm default risks in loan pricing is more likely in line with government policies contingent on the macroeconomic environment at that time, as the risk is in fact covered by government guarantees. Of course, moral hazard associated with bank lending behavior changes in occasional cases cannot be ruled out. Even without relaxing financial policies, banks have strong incentives to avoid pushing troubled firms into bankruptcy, or to avoid a balance sheet disclosure of nonperforming loans and writing down their assets. Moreover, easing financial policies during and after the crisis by regulators provides both the opportunity and the incentive for some banks to do so. Again, we can examine whether banks follow sound risk management measures only when more recent data are available in the future.

[21] The results are available upon request.

6. Conclusion

This paper studies banks' loan pricing behavior towards listed firms in China during 2003Q2-- 2013Q2. For this purpose, we combine a contract-specific dataset on bank loans with other financial information for firms listed on the Shenzhen and Shanghai Stock Exchange, and merge it with estimated corporate default risk series. By adopting the panel regression method, we find that banks charge higher loan rates for compensation if they are exposed to more severe default risks in general. Even so, banks' pricing strategies vary for different types of firms. While borrowing costs for SOEs appear to be unaffected by their default risks, Non-SOEs are required to compensate for their default risks when borrowing from banks. However, banks did not take into consideration the default risk of both SOEs and Non-SOEs after the Global Financial Crisis when government relief measures were still in effect. Furthermore, we find that the big four banks had a stronger obligation to come to the aid of SOEs than to that of Non-SOEs after the financial crisis. This is because bank loans, especially loans by the big four banks, act as a quasi-fiscal policy after the financial crisis, and such a policy tilted more towards SOEs. On the other hand, other banks appeared to be more aggressive in providing loans to Non-SOEs with less concerns on their default risks. The study also finds that the real estate sector and other government-supported industries enjoyed better terms on loan pricing in terms of default risks after the financial crisis. Nevertheless, banks required compensation for default risks from borrowing firms in these industries before the crisis, just as banks required compensation from firms in other industries. This means that the normal risk management practice prevailed in commercial lending during that period.

Overall, we provide new evidence on how the lending rate is affected by corporate borrowers' default risks in different aspects, which has important policy implications. Although banks provided liquidity to firms after the 2008 Global Financial Crisis that stabilized the financial system and economic growth, the excess liquidity provided with low borrowing standards had worsened the over-capacity problem, as witnessed by increasing debt-to-asset ratio for

SOEs after the financial crisis (Zhang et al. (2015)). Therefore, measures have to be taken to make firm debt sustainable, including good risk management practice in commercial lending. Of course, it is difficult to judge the soundness of bank risk management after the crisis based only on our data sample, as it only covers the period when the relief measures were still in effect. More recent data are required for such an analysis. In addition, further studies on other contract features in non-price terms, collectively known as “covenants”, are necessary to help us gain a better understanding of Chinese bank loan contracts.

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Appendix: Method to estimate *DLI*

Symbolically, the Merton model stipulates that firm asset follows a geometric Brownian motion

$$dV_t / V_t = \mu d_t + \delta_V dW_t \tag{A0}$$

The equity value of a firm satisfies the call option condition

$$E_t = V_t \mathrm{N}(d_1) - e^{-rT} D_t \mathrm{N}(d_1 - \delta\sqrt{T}) \tag{A1}$$

where *E* is the market value of firm equity, *F* is the synthesis of firm liabilities, acting as option's strike price, *V* is the firm's asset value, *r* is the instantaneous risk-free rate, *N(.)* is the cumulative standard normal distribution function. In addition, d_1 and d_2 are defined respectively as

$$d_1 = \frac{\ln(V_t/F_t) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{A2}$$

and

$$d_2 = d_1 - \sigma_V\sqrt{T} \tag{A3}$$

The distance to default *DD* can be calculated as

$$DD = \frac{\ln(V_t/F_t) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{A4}$$

where μ is an estimate of the expected annual return of the firm's assets. The corresponding implied default likelihood, *DLI,* is then defined as:

$$DLI = N\left[-\left(\frac{\ln(V_t/F_t) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)\right] = N(-DD) \tag{A5}$$

For default likelihood in 1-year horizon, *T=1* (year). In practice, *F* is the short-term debt plus a half of the long-term debt. Rather than apply the iterative method proposed by Bharath and Shumway (2008), we adopt the maximum likelihood estimation introduced by Duan (1994) to estimate *V*, δ, and μ with the following maximum likelihood function conditional on Equations (A1)--(A3):

$$\mathrm{L}(\mu, \delta) = -\left[\frac{n-1}{2}\right]\ln(2\pi) - \left[\frac{n-1}{2}\right]\ln(\delta^2)$$

$$-\sum_{t=2}^{n} lnV_t(\delta) - \sum_{t=2}^{n} lnN(d_t) \; - \sum_{t=2}^{n}(lnV_t(\delta) - lnV_{t-1}(\delta) - u)^2 \tag{A6}$$

Figures

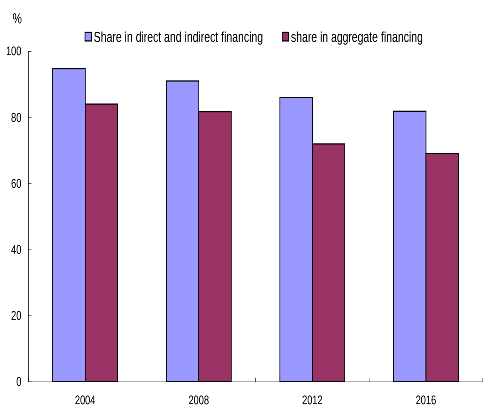
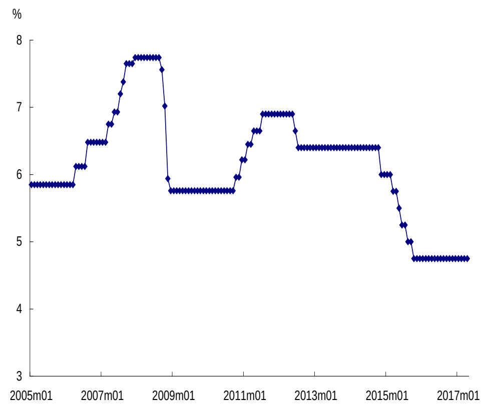
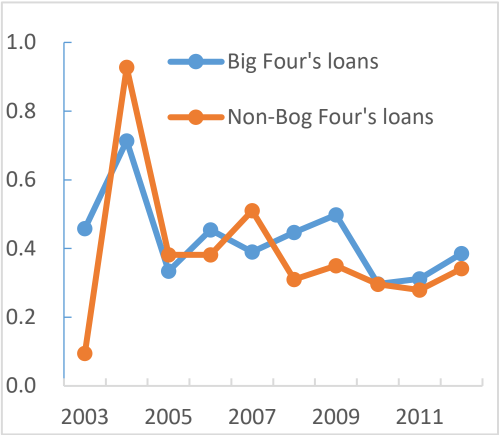
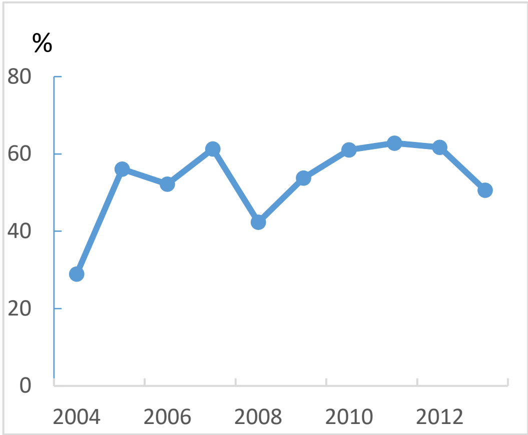
Figure 1: Size of commercial loans	Figure 2: China’s 5-year lending rate
	
Source: CEIC and staff estimates	Source: CEIC and staff estimates

Figure 3: Loans to SOEs relative to Non-SOEs	Figure 4: Share of loans to government-supported firms
	
Source: WIND and staff estimates	Source: WIND and staff estimates

Tables

Table 1: Summary statistics of variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Lrate (%)	12039	6.32	1.40	0.00	26.10
DLI	11291	0.15	0.21	0.00	1.00
Lsize	12039	17.64	1.47	8.01	22.86
Brate (%)	12039	6.23	0.77	4.86	7.83
Lterm	12038	3.90	3.65	0.16	30.00
RRR (%)	12039	15.14	3.60	6.00	21.00
Tangble	12039	0.60	0.13	0.07	1.00
MTB	11982	1.00	0.01	0.86	1.08
Lev	12039	1.58	0.33	0.12	4.54

Sources: Bloomberg, CEIC and authors' estimates

Table 2: Correlations between independent variables

	DLI	*Lsize*	*Brate*	*Lterm*	*RRR*	*Tangble*	*MTB*	*Lev*
DLI	1							
Lsize	0.06	1						
Brate	0.11	-0.03	1					
Lterm	-0.03	0.29	0.25	1				
RRR	0.1	0.12	-0.14	-0.18	1			
Tangble	-0.04	-0.06	0.01	-0.02	-0.08	1		
MTB	0	-0.04	0	-0.03	-0.03	0.21	1	
Lev	-0.16	-0.17	-0.06	-0.04	-0.02	0.12	-0.05	1

Sources: Authors' estimates.

Table 3: Benchmark Regressions for loan pricing

	RegA1	RegA2	RegA3
DLI	0.154**	0.119*	0.138**
	(0.0638)	(0.0647)	(0.0656)
Lsize	-0.0376***	-0.0375***	-0.0382***
	(0.0111)	(0.0110)	(0.0109)
Brate	0.488***	0.490***	0.484***
	(0.0263)	(0.0263)	(0.0263)
Lterm	0.00529	0.00587	0.00678*
	(0.00367)	(0.00368)	(0.00366)
RRR		0.0382***	0.0409***
		(0.0108)	(0.0109)
Tangble			-0.780***
			(0.227)
MTB			-3.846*
			(2.301)
Lev			-0.278***
			(0.0818)
Observations	10,944	10,944	10,898
R-squared	0.491	0.492	0.495

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 4: Pricing of loans to SOE and Non-SOEs

	RegB1	RegB2	RegB3	RegB4
	SOEs	SOEs	Non-SOEs	Non-SOEs
DLI	0.0463	-0.00261	0.193**	0.161**
	(0.116)	(0.117)	(0.0766)	(0.0798)
Lsize	-0.0864***	-0.0805***	-0.0179	-0.0215
	(0.0158)	(0.0159)	(0.0143)	(0.0140)
Brate	0.494***	0.483***	0.484***	0.483***
	(0.0542)	(0.0542)	(0.0302)	(0.0302)
Lterm	0.00435	0.00357	0.00718	0.00937*
	(0.00512)	(0.00519)	(0.00512)	(0.00508)
RRR		0.0547***		0.0422***
		(0.0175)		(0.0136)
Tangble		-1.687***		-0.429
		(0.448)		(0.267)
MTB		8.299**		-7.487***
		(3.327)		(2.638)
Lev		-0.127		-0.289***
		(0.135)		(0.0973)
Observations	3,173	3,162	7,771	7,736
R-squared	0.498	0.505	0.503	0.508

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 5: Loan pricing before and after financial crisis

	RegC1	RegC2	RegC3	RegC4	RegC5	RegC6
	Whole	Whole	SOEs	SOEs	Non-SOEs	Non-SOEs,
	T<2008Q2	T>2008Q1	T<2008Q2	T>2008Q1	T<2008Q2	T>2008Q1
DLI	0.353***	0.0283	0.314	-0.0606	0.468***	0.0853
	(0.119)	(0.0826)	(0.211)	(0.146)	(0.147)	(0.0983)
Lsize	-0.0672***	-0.0291**	-0.098***	-0.0483**	-0.0578**	-0.0156
	(0.0169)	(0.0128)	(0.0273)	(0.0197)	(0.0224)	(0.0158)
Brate	0.235***	0.568***	0.656***	0.539***	0.00523	0.573***
	(0.0799)	(0.0371)	(0.150)	(0.0686)	(0.0888)	(0.0440)
Lterm	0.00711	0.0197***	-0.0249**	0.0207***	0.0263***	0.0181***
	(0.00608)	(0.00441)	(0.0102)	(0.00623)	(0.00726)	(0.00586)
RRR	0.0175	0.0804***	-0.0598	0.101***	0.0606*	0.0849***
	(0.0291)	(0.0164)	(0.0490)	(0.0257)	(0.0360)	(0.0198)
Tangble	-1.935***	-0.704**	-2.579***	-2.368***	-1.538***	-0.0716
	(0.430)	(0.355)	(0.710)	(0.671)	(0.561)	(0.409)
MTB	5.862	-13.00***	9.978	7.588*	5.459	-19.15***
	(3.633)	(4.784)	(9.258)	(4.366)	(4.239)	(5.848)
Lev	-0.0313	-0.304***	0.219	-0.302	-0.116	-0.276**
	(0.165)	(0.110)	(0.241)	(0.206)	(0.263)	(0.120)
Observations	3,051	7,814	1,111	2,041	1,939	5,773
R-squared	0.512	0.548	0.572	0.509	0.495	0.575

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 6: Loan pricing by the Big-Four banks

	RegD1	RegD2	RegD3	RegD4	RegD5	RegD6
	SOEs	Non-SOEs	SOEs	SOEs	Non-SOEs	Non-SOEs
			T<2008Q2	T>2008Q1	T <2008Q2	T >2008Q1
DLI	0.0666	0.209*	0.401**	0.113	0.0113	0.258**
	(0.210)	(0.121)	(0.198)	(0.154)	(0.190)	(0.121)
Lsize	-0.0694***	-0.036***	-0.0743**	-0.0250	-0.0351	-0.0313*
	(0.0221)	(0.0129)	(0.0342)	(0.0215)	(0.0246)	(0.0177)
Brate	0.620***	0.545***	0.543***	0.619***	0.259**	0.559***
	(0.0428)	(0.0250)	(0.171)	(0.0609)	(0.112)	(0.0518)
Lterm	-0.0167*	-0.00484	-0.0232*	-0.00441	-0.00169	0.00404
	(0.00870)	(0.00608)	(0.0126)	(0.00655)	(0.00909)	(0.00592)
RRR	0.0593*	-0.00339	0.0148	0.127***	-0.00510	0.0292
	(0.0316)	(0.00892)	(0.0589)	(0.0287)	(0.0418)	(0.0204)
Tangble	-0.705*	-1.040***	-2.409***	-1.031**	-1.706**	-0.667**
	(0.410)	(0.336)	(0.807)	(0.522)	(0.786)	(0.329)
MTB	10.11*	-0.329	3.585	12.31**	6.813	-5.804**
	(5.390)	(2.415)	(13.93)	(4.998)	(5.214)	(2.776)
Lev	0.0340	-0.154	-0.251	0.252	-0.495	-0.160
	(0.241)	(0.143)	(0.271)	(0.265)	(0.306)	(0.141)
Observations	1,875	4,222	726	1,141	1,195	3,001
R-squared	0.590	0.573	0.615	0.594	0.528	0.603

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 7: Loan pricing by the Non-Big-Four banks

	RegE1	RegE2	RegE3	RegE4	RegE5	RegE6
	SOEs	Non-SOEs	SOEs T<2008Q2	SOEs T>2008Q1	Non-SOEs T <2008Q2	Non-SOEs T >2008Q1
DLI	0.403	0.0631	1.074	0.373	1.155***	-0.0753
	(0.280)	(0.233)	(0.760)	(0.239)	(0.294)	(0.166)
Lsize	-0.0275	0.0140	-0.122**	0.0201	0.0309	0.0365
	(0.0447)	(0.0336)	(0.0484)	(0.0409)	(0.0515)	(0.0283)
Brate	0.284***	0.454***	1.055***	0.399**	-0.167	0.624***
	(0.0907)	(0.0766)	(0.329)	(0.170)	(0.172)	(0.0753)
Lterm	0.0200*	-0.00807	-0.0471**	0.0351***	0.0304**	-0.0172
	(0.0105)	(0.0131)	(0.0191)	(0.0119)	(0.0134)	(0.0108)
RRR	0.0477	0.0737***	-0.284***	0.147***	0.0790	0.103***
	(0.0360)	(0.0270)	(0.107)	(0.0547)	(0.0724)	(0.0371)
Tangble	-3.099*	-0.350	-3.906*	-3.226**	-2.611**	0.261
	(1.583)	(0.539)	(2.209)	(1.277)	(1.115)	(0.742)
MTB	18.95**	-2.207	34.75**	11.69	20.97***	-3.278
	(7.691)	(5.194)	(13.75)	(7.666)	(7.173)	(6.787)
Lev	-0.501	-0.630**	0.720	-0.987***	0.863*	-0.545**
	(0.465)	(0.293)	(0.595)	(0.331)	(0.520)	(0.250)
Observations	1,307	3,726	396	903	872	2,831
R-squared	0.509	0.488	0.526	0.555	0.482	0.543

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 8: Loan pricing for the real estate sector

	RegF1	RegF2	RegF3
	Whole sample	T <2008Q2	T >2008Q1
DLI	0.235***	0.355***	0.175**
	(0.0664)	(0.122)	(0.0804)
DLI_RET	-0.495**	-0.0385	-0.594***
	(0.200)	(0.491)	(0.222)
Lsize	-0.0387***	-0.0672***	-0.0305**
	(0.0109)	(0.0170)	(0.0127)
Brate	0.482***	0.234***	0.568***
	(0.0263)	(0.0800)	(0.0369)
Lterm	0.00652*	0.00711	0.0196***
	(0.00366)	(0.00608)	(0.00441)
RRR	0.0405***	0.0174	0.0798***
	(0.0109)	(0.0290)	(0.0163)
Tangble	-0.755***	-1.932***	-0.699**
	(0.228)	(0.427)	(0.355)
MTB	-4.227*	5.812*	-12.92***
	(2.309)	(3.460)	(4.768)
Lev	-0.263***	-0.0304	-0.275**
	(0.0823)	(0.165)	(0.111)
Observations	10,898	3,051	7,814
R-squared	0.496	0.512	0.549

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 9: Loan pricing across industries

	RegG1	RegG2	RegG3	RegG4	RegG5	RegG6
	G-Support Whole sample	G-support T<2008Q2	G-support T>2008Q1	Others Whole sample	Others T<2008Q2	Others T >2008Q1
DLI	-0.0110	0.293*	-0.114	0.277***	0.432**	0.148*
	(0.107)	(0.158)	(0.148)	(0.0792)	(0.189)	(0.0873)
Lsize	-0.0493***	-0.0858***	-0.0244	-0.0401***	-0.0574***	-0.0434***
	(0.0171)	(0.0295)	(0.0212)	(0.0134)	(0.0213)	(0.0150)
Brate	0.407***	0.324***	0.503***	0.528***	0.310***	0.561***
	(0.0501)	(0.125)	(0.0728)	(0.0303)	(0.105)	(0.0429)
Lterm	0.0140***	0.0211***	0.00611	0.0114	-0.0559***	0.0533***
	(0.00423)	(0.00715)	(0.00573)	(0.00743)	(0.0167)	(0.00795)
RRR	0.103***	0.0458	0.136***	0.000505	-0.0425	0.0438**
	(0.0205)	(0.0450)	(0.0331)	(0.0123)	(0.0390)	(0.0173)
Tangble	-0.705**	-1.903***	-0.350	-0.358	-1.473**	-0.618*
	(0.350)	(0.597)	(0.595)	(0.290)	(0.733)	(0.372)
MTB	-1.146	7.216	-10.15**	-7.541*	2.843	-18.43*
	(2.535)	(4.802)	(4.015)	(4.549)	(4.565)	(11.02)
Lev	-0.412***	0.0685	-0.599***	0.0252	0.283	0.183
	(0.130)	(0.238)	(0.167)	(0.102)	(0.255)	(0.140)
Observations	4,067	1,153	2,898	6,829	1,896	4,914
R-squared	0.481	0.536	0.537	0.535	0.514	0.585

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors’ estimates.

Table 10: Pricing of loans to SOE and Non-SOEs (50% cutoff)

	RegB1'	RegB2'	RegB3'	RegB4'
	SOEs	SOEs	Non-SOEs	Non-SOEs
DLI	0.0390	-0.0350	0.152**	0.142**
	(0.149)	(0.150)	(0.0699)	(0.0721)
Lsize	-0.0769***	-0.0738***	-0.0253*	-0.0279**
	(0.0181)	(0.0181)	(0.0134)	(0.0132)
Brate	0.387***	0.373***	0.520***	0.518***
	(0.0683)	(0.0691)	(0.0282)	(0.0283)
Lterm	0.0123*	0.0141**	0.00448	0.00609
	(0.00627)	(0.00643)	(0.00443)	(0.00444)
RRR		0.0902***		0.0302**
		(0.0212)		(0.0126)
Tangble		-1.063**		-0.729***
		(0.504)		(0.259)
MTB		7.588		-5.127**
		(5.305)		(2.446)
Lev		-0.323**		-0.263***
		(0.149)		(0.0949)
Observations	2,371	2,361	8,573	8,537
R-squared	0.523	0.530	0.491	0.495

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 11: Loan pricing before and after financial crisis (50% cutoff)

	RegC1’	RegC2’	RegC3’	RegC4’	RegC5’	RegC6’
	Whole	Whole	SOEs	SOEs	Non-SOEs	Non-SOEs,
	T<2008Q2	T>2008Q1	T<2008Q2	T>2008Q1	T<2008Q2	T>2008Q1
DLI	0.353***	0.0283	0.687**	-0.0543	0.321**	0.0847
	(0.119)	(0.0826)	(0.320)	(0.184)	(0.126)	(0.0909)
Lsize	-0.0672***	-0.0291**	-0.080***	-0.0352	-0.059***	-0.0255*
	(0.0169)	(0.0128)	(0.0306)	(0.0223)	(0.0210)	(0.0150)
Brate	0.235***	0.568***	0.841***	0.448***	0.0449	0.596***
	(0.0799)	(0.0371)	(0.183)	(0.0913)	(0.0832)	(0.0408)
Lterm	0.00711	0.0197***	-0.0320*	0.0217***	0.0156**	0.0218***
	(0.00608)	(0.00441)	(0.0163)	(0.00747)	(0.00649)	(0.00538)
RRR	0.0175	0.0804***	-0.121**	0.129***	0.0617*	0.0726***
	(0.0291)	(0.0164)	(0.0601)	(0.0309)	(0.0327)	(0.0188)
Tangble	-1.935***	-0.704**	-2.430***	-1.827**	-1.700***	-0.463
	(0.430)	(0.355)	(0.784)	(0.755)	(0.525)	(0.398)
MTB	5.862	-13.00***	27.59**	10.47	5.196	-16.19***
	(3.633)	(4.784)	(10.99)	(6.366)	(3.883)	(5.287)
Lev	-0.0313	-0.304***	0.0831	-0.455*	0.0126	-0.296**
	(0.165)	(0.110)	(0.269)	(0.236)	(0.243)	(0.118)
Observations	3,051	7,814	796	1,558	2,255	6,256
R-squared	0.512	0.548	0.659	0.506	0.471	0.566

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors’ estimates.

Table 12: Loan pricing by Big Four banks (50% cutoff)

	RegD1'	RegD2'	RegD3'	RegD4'	RegD5'	RegD6'
	SOEs	Non-SOEs	SOEs	SOEs	Non-SOEs	Non-SOEs
			T<2008Q2	T>2008Q1	T <2008Q2	T >2008Q1
DLI	0.0473	0.173*	0.911***	0.0488	-0.0137	0.276**
	(0.338)	(0.0959)	(0.263)	(0.188)	(0.154)	(0.113)
Lsize	-0.0621**	-0.043***	-0.0420	-0.0233	-0.0452*	-0.0335*
	(0.0246)	(0.0124)	(0.0386)	(0.0220)	(0.0234)	(0.0173)
Brate	0.503***	0.592***	0.606***	0.616***	0.296***	0.563***
	(0.0426)	(0.0262)	(0.209)	(0.0662)	(0.104)	(0.0485)
Lterm	-0.00177	-0.0130**	-0.0163	-0.00221	-0.00996	0.00245
	(0.00941)	(0.00636)	(0.0186)	(0.00675)	(0.00829)	(0.00561)
RRR	0.108***	-0.0106	-4.61e-05	0.130***	-0.00610	0.0300
	(0.0242)	(0.0116)	(0.0712)	(0.0308)	(0.0384)	(0.0196)
Tangble	-0.182	-1.169***	-1.949**	-0.792	-1.753**	-0.872***
	(0.473)	(0.301)	(0.827)	(0.544)	(0.752)	(0.322)
MTB	10.29	0.379	13.59	13.79**	6.316	-3.665
	(7.474)	(2.190)	(17.85)	(6.760)	(4.925)	(2.570)
Lev	-0.128	-0.0942	-0.368	0.216	-0.393	-0.147
	(0.211)	(0.145)	(0.284)	(0.271)	(0.282)	(0.141)
Observations	1,413	4,684	501	905	1,420	3,237
R-squared	0.657	0.553	0.722	0.624	0.496	0.595

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors' estimates.

Table 13: Loan pricing by Non-Big-Four banks (50% cutoff)

	RegE1’	RegE2’	RegE3’	RegE4’	RegE5’	RegE6’
	SOEs	Non-SOEs	SOEs	SOEs	Non-SOEs	Non-SOEs
			T<2008Q2	T>2008Q1	T <2008Q2	T >2008Q1
DLI	0.441	0.0898	1.775*	0.419	0.946***	-0.0572
	(0.367)	(0.217)	(0.965)	(0.310)	(0.276)	(0.154)
Lsize	0.00699	-0.00295	-0.117**	0.0759	0.0242	0.0194
	(0.0529)	(0.0312)	(0.0547)	(0.0466)	(0.0480)	(0.0270)
Brate	0.176	0.457***	1.346***	0.273	-0.137	0.615***
	(0.138)	(0.0721)	(0.377)	(0.269)	(0.163)	(0.0692)
Lterm	0.0302**	-0.00598	-0.0476	0.0367**	0.0195*	-0.0114
	(0.0141)	(0.0113)	(0.0328)	(0.0175)	(0.0115)	(0.00918)
RRR	0.0473	0.0726***	-0.438***	0.179**	0.0928	0.101***
	(0.0479)	(0.0263)	(0.116)	(0.0699)	(0.0674)	(0.0348)
Tangble	-2.397	-0.822	-5.481**	-2.207	-2.418**	-0.324
	(2.140)	(0.508)	(2.406)	(1.672)	(1.044)	(0.692)
MTB	17.93	0.636	116.1**	14.24	20.30***	-1.751
	(18.58)	(5.133)	(51.77)	(12.08)	(6.639)	(6.151)
Lev	-0.605	-0.624**	0.368	-1.419***	0.822*	-0.504**
	(0.596)	(0.290)	(0.573)	(0.491)	(0.485)	(0.240)
Observations	965	4,067	305	656	963	3,078
R-squared	0.514	0.486	0.562	0.560	0.477	0.542

Note: Heteroskedasticity-robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Source: Authors’ estimates.

Table 14: Consistency check for risk premium after resampling

	consistency ratio
Resample for RegB3 relative to RegB1	16/30
Resample for RegB4 relative to RegB2	11/30
Resample for RegC2 relative to RegC1	26/30
Resample for RegC5 relative to RegC3	20/30
Resample for RegC6 relative to RegC4	28/30
Resample for RegC6 relative to RegC5	24/30
Resample for RegD2 relative to RegD1	6/30
Resample for RegD4 relative to RegD3	20/30
Resample for RegD5 relative to RegD3	28/30
Resample for RegD6 relative to RegD4	10/30
Resample for RegD6 relative to RegD5	8/30
Resample for RegE2 relative to RegE1	28/30
Resample for RegE5 relative to RegE3	28/30
Resample for RegE6 relative to RegE5	25/30
Resample for RegG4 relative to RegG1	28/30
Resample for RegG3 relative to RegG2	23/30
Resample for RegG6 relative to RegG3	13/30
Resample for RegG6 relative to RegG5	10/30

Source: Authors' estimates.