Does Informal Finance Help Formal Finance? Evidence from Third Party Loan Guarantees in China

ABSTRACT

Building on the important study by Allen, Qian and Qian (2005) and Ayyagari, Demirgüc-Kunt and Maksimovic (2010), we examine whether third party guarantors play an effective role in assessing loan risk. Using a proprietary database of third party loan guarantees in China, we find strong evidence that guarantors and banks disagree on pricing loan risk, and that banks can better predict loan defaults than guarantors. We also find that the probability of loan default is affected by the capability of guarantor officers. Our findings question the contribution of soft information in the improvement of credit scoring and support the view that informal finance should be limited. This paper also supports the implications of studies on human capital in financial intermediation.

Key words: Third party guarantee; Informal finance; Loan default; Soft information

JEL Classification: G21, G14, D81, D82, H81

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I. Introduction

Bank lending to small and medium enterprises is attracting attention from both researchers and practitioners. China's economy is populated with a very large number of small and medium enterprises, which contribute substantially to its national economy (Chong, Lu and Ongena, 2010). While existing literature is showing that many of the state-owned banks' loans were originated to state-owned enterprises (Chang, Liao, Yu and Ni, 2010). A large number of small private firms in China are faced with difficulties of obtaining bank loans. Under these circumstances, the third party guarantor is playing a key role bridging small borrowers and banks. Third party loan guarantee business has grown to be a competitive market in China. However, as an important form of alternative financing channel, guaranteed loans are rarely discussed in literature. Few studies have discussed the role played by guarantors in assessing loan risk and the information collection and transmission in the lending process.

A strand of literature shows the existence of informal finance alongside formal systems. Recent work by Tsai (2002), Allen, Qian and Qian (2005), and Linton (2006) argue that private sector firms in China rely on alternative financing and governance mechanisms. It is the informal finance that contributes to the fast growing of private sectors. However, Ayyagari, Demirgüc-Kunt and Maksimovic (2010) provides counter evidence that firms with formal financing channels grow faster than those with alternative finance. Their findings question whether reputation and relationship-based financing is responsible for the performance of the fastest-growing firms in developing countries.

In this article we use detailed third party guaranteed loan data on small firms in China to investigate which of the two views are consistent with the operation of the informal sector in China. Specifically, in a setting with information asymmetry among borrower, guarantors and banks, do banks agree with guarantors in pricing loan risk? Who is better able to predict the probability of loan default, the guarantor or the bank? To answer these questions, we first investigate how loan rates are correlated with rates of guarantee fee. Next, we explore the determinants of rates of guarantee fee and guaranteed amount. We then study whether loan rates and rates of guarantee fee have predictive power on loan default. Finally, we examine whether guarantors and banks use the same sources of information when assessing borrower credit quality.

The dataset we use covers third party guaranteed loans from 2006 to the first half of 2009. The advantage of this dataset is its coverage of Chinese small and medium enterprises (SMEs). In addition to financial information and loan characteristics of borrowers, the dataset also includes private information collected by guarantors, as well as guarantor officers' characteristics. These merits of the dataset allow me to investigate various factors affecting loan pricing and probability of loan default.

Using rates of guarantee fee and loan rates as the measure of information used by guarantors and banks respectively, we find that guarantors and banks disagree on the pricing of loans. Specifically, higher loan rates set by banks negatively correlate to lower default probability measure given by the guarantor. This result suggests guarantors and banks rely on different information in assessing borrower's risk. With the responsibility to recover major loss when borrowers default on loans, guarantors have incentives to explore as much information about borrowers operation and credit quality as they can, while banks mainly rely on accounting data reported by borrowers and public information provided by rating agencies.

Our results also show that loan rates have predictability of loan default, while rates of guarantee fee do not. This finding is supported by the probit regression results for default prediction. These results remain robust after controlling for fixed year and industry effects. As suggested by Cerqueiro, Degryse and Ongena (2011) that decentralized, small banks have a comparative advantage in the production of soft information because soft information is costly to acquire and difficult to transmit to others, we expect the guarantor is in a better position to collect soft information about borrowers, since guarantors are small private firms compared with lending banks. Another interesting finding is that the probability of loan default is affected by capability of guarantor officers. This result sheds light on the importance of human capital for financial sectors[1].

The dominant view on the role of soft information in bank lending literature is that it is the soft information component that contributes to the improvement of credit assessment (Chang, Liao, Yu and Ni, 2010). Qian, Strahan and Yang (2010) also find that soft information has a more pronounced effect relative to publicly available information when banks make lending decisions. If similar results hold in the cases where loans are guaranteed by a third party guarantor, we should expect guarantors can predict loan default more precisely because guarantors have greater incentives to explore private information about the borrowers. However, the empirical results question the importance of soft information in pricing loans.

[1] See, for example, Hertzberg, Liberti and Paravisini (2010), Bellucci, Borisov, and Zazzaro (2010).

We further examine the information content of rates of guarantee fee, default probability measure and loan rates. Empirical results indicate that guarantors incorporate soft information when making guarantee decisions, while banks rely more on public information and ratings. We also find evidence that it is the additional part of information banks have than guarantors that contributes to the predictability of loan default. A possible explanation is that although guarantors have advantage over banks in terms of analyzing borrowers' credit risk by utilizing soft information, banks may have overwhelming advantage in collecting and analyzing hard information about borrowers.

Overall, our findings are consistent with implications of literature questioning the contribution of informal financing in China. Ayyagari, Demirgüc-Kunt and Maksimovic (2010) found bank financing, or formal financing is associated with faster growth. The existence of guarantors is also a special form of intermediation adapted to the poor finance and law environment in developing economies such as China. We doubt whether guarantors serve as an efficient supplement to the formal banking system.

This work may contribute to literature in the following senses: First, it analyzes the role of third party loan guarantor in bridging small borrower and banks; second, it provides both theoretical and empirical analysis of information asymmetry among all participants in the lending process. Results in this article is based on first-hand data on guaranteed loans in China, and have policy implications that informal finance needs to be regulated and limited.

The rest of the paper proceeds as follows: Section II discusses the practice of bank lending in China and theoretical background, as well as hypothesis development; Section III describes the data and sample characteristics; Section IV presents empirical results on disagreement between guarantors and banks; Section V analyzes the prediction of loan default; Section VI explores the information content of rates of guarantee fee and loan rates; Section VII concludes.

II. Institutional Background and Hypothesis Development

A. Third Party Loan Guarantee

China's banking sector has been the primary source of financing for China's growing economy, with the banking and credit industry accounting for over 80 percent of China's financial assets (Bailey et al., 2010). According to the website of the China Banking Regulatory Commission, in 2009 the GDP grew by 8.7 percent and reached RMB 33.5 trillion, while the outstanding balance of loans made by banking institutions increase by RMB 10.5 trillion or 33.0 percent year-on-year to RMB 42.6 trillion. Total bank loans comprised 127.16% of GDP. With bank loans accounting for 87% of total funds raised by China's non-financial sector as of June 2006, bank lending remains the dominant source of financing in China's economy (Bailey et al., 2010).

As of end-2009, China' banking sector comprises 2 policy banks and China Development Bank (CDB), 5 large commercial banks (Agriculture Bank of China, Bank of China, China Construction Bank, Industrial and Commercial Bank of China, and Bank of Communications), 12 joint-stock commercial banks, 143 city commercial banks, 43 rural commercial banks, and other forms of banking institutions. The four largest, state-owned commercial banks have nation-wide networks of branches and control the majority of assets in the banking system, although their dominant status has been weakened in recent years, with the gradual opening of China banking system as a result of China's entrance to WTO in 2001 (Qian et al., 2010).

To introduce competition among banks and improve the banking sector's efficiency, China opened its domestic currency (RMB) business to all foreign banks by 2006. The "big four", along with join-stock banks and foreign banks are sharing the majority of banking business. However, the "big four" are still accounting for overwhelming proportion in terms of both asset scale as well as loan size. Many of the state-owned banks' loans were originated to state-owned enterprises (SOEs) based on political and policy considerations (Chang et al., 2010). Bank lending continues to be driven by the availability of funds, not borrower profitability (Bailey et al., 2010). A large number of small enterprises are still facing difficulties in obtaining bank loans. Recognizing the obstacles that small enterprises are faced with, the Chinese government raised this issue to the national development agenda which resulted in the "Small and Medium Enterprises (SMEs) Promotion Law" in 2003. However, small firms financing difficulties persist. Chong et al. (2010) reported the 2005 survey results that among the SMEs owners that responded, 79.5% of them rated financing environment as "not change" or "deteriorating" compared with the years prior to 2005.

For small firms which can not obtain loans directly from a bank, they probably would need to find a guarantor to provide loan guarantee to them. In this case, the guarantor is taking over part of the certification role played by banks.

The guarantor plays a key role in the lending process. Since its business depends on how precisely it can predict loan defaults, it has an incentive to investigate these borrowers and get as much useful information as they can. Although we use a propriety database owned by one Chinese guarantee company, the basic principles and evaluating process it adopts would not differ much across different guarantors, since they are operating according to uniform laws and regulations. When evaluating a guarantee application, a guarantor officer would give two scores: the qualitative score, based on the officer's subjective judgment of the borrower's market power, competitiveness, credit worthiness, etc; the quantitative score, calculated by a formula with accounting data as major inputs. Then, combined with loan information, including amount of loan applied for, term of loan and value of collateral, the officer would then compute an overall default probability measure. The default probability measure is mapped to certain level of rate of guarantee fee. Normally, a higher default probability measure corresponds to higher rate of guarantee fee. After a guarantee application is approved by the guarantor, the lending bank would decide a loan rate based on its judge on the loan quality. While the lending bank may or may not take the rate of guarantee fee into consideration when deciding the loan rate, the guarantor would not adjust its pricing of the loan guarantee[2].

In my dataset, there are zero rates of guarantee fee in some cases. I exclude theses cases in the major analysis since they refer to special government-funded projects, which are different from most of the cases. This paper mainly focuses on the cases where the source of funds is commercial banks.

B. Theoretical Framework

[2] In practice, there are few cases where borrowers reject bank loans because of high loan rates. This rules out the possibilities that any conflicts in the pricing by guarantors and banks are due to borrowers with high loan rates dropping out of the sample.

An important role of financial intermediary is to mitigate problems such as transaction costs, information asymmetries and agency conflicts. Literature has recognized the superior ability of banks in acquiring information or knowledge beyond that which is available to ordinary financial market participants (e.g., Ramakrishnan and Thakor 1984, Diamond 1984, Boyd and Prescott 1986, and Dow and Gorton 1997). When banks and prospective borrowers are independent and profit-maximizing, banks would serve to generate information and play the certification role in issuing debt. However, as suggested by Bailey et al. (2010), the poor state of law, regulation, and discloser in China's capital market is a severe constraint on the efficiency of banks and borrowers. Moreover, interest rates on bank loans are regulated by the government and are not effectively linked to borrower credit ratings. Under theses circumstances, the signaling value of bank loans is no longer obvious.

In small firms' borrowings, the content of loan rates is mainly composed of hard information since it is the guarantor that has the incentive to exert efforts and improve the accuracy of credit ratings. In China, most guarantors are private firms rather than a division of lending banks. Guarantee fee is the major source of income of guarantors. It pursues the goal of profit-maximization by minimizing the payments for default loans. Therefore, guarantors have incentives to collect all types of information about borrowers, such as the number of shareholders, whether the firm managers have a political background, etc. to help the scoring process. In this sense, guarantors have superior soft information about borrowers. I am interested in asking, does guarantors' soft information really help in predicting loan defaults? Objectively, guarantors would score borrowers and price guaranteed loans solely based on its default probability measure. However, in real business setting, guarantee applications are processed by individual guarantor officers. Conflicts of interest between individual guarantor officers' pursuing personal benefits and realizing the firm's profit-maximization goal can arise. This issue can potentially affect guarantors' evaluation of borrowers' credit condition.

On the banks' side, there are a number of empirical studies linking bank's information to loan default prediction. Do banks rely on the information provided by guarantors? In 2004 Chinese banks started to implement an internal credit rating system. Chang et al. (2010) suggested that internal credit ratings are significantly related to the commonly used firm-specific financial factors in predictable ways. They found that while bank's internal credit ratings largely subsume firm-specific hard information, it is the soft information component of these ratings that contributes to the improvement in assessing credit quality. Qian et al. (2010) also suggested that with a series of reforms implemented in banking sector in China, loan officers have stronger incentives to produce high-quality soft information. An increasing number of studies show that banks are using more soft information nowadays. However, in the cases where guarantors take over the role of investigating and screening borrowers, do banks still have incentives to collect soft information? To what extent does soft information owned by guarantors contributes to the assessment of loan risks? This paper aims to address these questions. Given that the information content of loan rates and rates of guarantee fee can be different, I expect they would lead to different prediction of loan defaults.

The potential asymmetric information problems in the lending process are as follows: first, Borrowers have incentives to lie, for example, to manipulate accounting information or to hide bad information from both guarantor and banks[3]; second, guarantors have incentives to hide good information from banks, or it will lose good business; third, banks have incentives to hide bad information from the guarantor. Since banks do not take the cost of default, it only cares about the interest income from loans.

A number of studies have been discussing information asymmetry in bank lending. Mankiw (1986) analyzed the inefficiency in allocation of credit because borrowers have greater information concerning their own riskiness than do lender. Although the asymmetry always exists, banks may gain an information advantage that allows them to impose higher interest rates by monitoring borrowers, argued by Rajan (1992). However, there is little literature discussing information asymmetry between borrowers and guarantors.

This section contains a simple model between a borrower and a guarantor. The firm desires a loan for its investment project, and is maximizing net amount of loan. The guarantor has to measure the riskiness of the loan and to decide whether to provide guarantee to the loan and the rate of guarantee fee. Once the guarantee application of the firm is submitted, the banker (a loan officer) will examine the creditworthiness of the borrower and decide upon a loan rate to charge.

Assume there are two types of borrowers: good and bad. Denote the probability of a good borrower occurring with P. Let R_g *and* R_b denote the guarantee rate and loan rate, respectively. Based on the above analysis, the borrower's problem can be expressed as follows:

[3] In our sample, we find cases where the borrower exaggerates its book value of shareholder equity and defaults on its loan. The empirical test for the hypothesis that borrowers have incentives to lie is presented in Section III.

$$\max\ L(1 - R_g - R_b)\ ,$$

where L stands for the amount of guarantee it applies for. For simplicity, assume the loan size never changes during the whole lending process. That is, the guarantor can only accept or reject a guarantee application, but can not change the amount of guarantee.

Given the guarantee application process in practice, information about the borrower comes from the investigation of the guarantor officer. It consists of public information such as accounting data reported by the borrower, private information such as number of shareholders and managers' political background, and subjective scoring of the borrowers' overall operation and creditworthiness by the loan officer. Let I denote the set of information the guarantor can get access to. With the incentive to get as much as net amount of loan, a bad borrower may have incentives to manipulate the information it provides, or, it has an incentive to lie. Let θ denote the probability that a bad borrower lying. In the investigation of the borrower, a guarantor may or may not detect the liar. Assume the guarantor can correctly judge the borrower's type with a probability of α. Since it is assumed that only bad borrowers would lie and the guarantor only lend to good borrowers, a guarantee application would be rejected once the guarantor finds that the borrower is lying. Let $P(\theta)$ denote the probability that the guarantor observes a good type borrower. The profit-maximization problem of the guarantor has the following expression:

$$\max imize\ E\{p(\theta)R_g L - [1 - p(\theta)]L\},$$

where $p(\theta) = p\alpha + (1-p)(1-\alpha)\theta$, θ is a function of α.

Differentiating the first-order condition with respect to θ and α, respectively, for the borrower's problem and the guarantor's problem[4], we obtain that (1) $\frac{\partial R_g}{\partial \theta}>0$ and (2) $\frac{\partial \theta}{\partial \alpha}<0$. The key variable α is affected by the expertise and information gathering ability of the guarantor. Information learning by guarantors from banks can improve the guarantor's ability to correctly judge on the borrowers' type[5]. If the guarantor is better able to judge borrowers' quality, borrower would have less incentive to lie, thus information asymmetry can be mitigated. Lower incentives to lie would benefit borrowers in the sense that it would reduce the average guarantee fee to be charged. On the guarantor's side, the less asymmetric information there is between it and the borrowers, the more precise its default prediction would be.

C. Hypothesis Development

The above framework suggests both guarantors and banks may make mistakes in predicting loan prospects. It gives rise to two sets of empirical predictions. The first is related to the possible disagreement between banks and guarantors on risk assessment.

Hypothesis1. Guarantors and banks may price loans differently based on different on sources of information they have.

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[4] It can be shown that $FOC(\theta){:}-\frac{\partial R_g}{\partial P(\theta)}\cdot\frac{\partial P(\theta)}{\partial \theta}-\frac{\partial R_g}{\partial \theta}=0$ and

$$FOC(\alpha): p(\theta)R_g+(1-p)(1-\alpha)R_g\frac{\partial \theta}{\partial \alpha}+(1-p)(1-\alpha)\frac{\partial \theta}{\partial \alpha}=0$$

[5] Here we implicitly assume that banks hold incomplete but true information about borrowers. This assumption is realistic regarding banks mainly rely on the internal credit system when judging a borrower. Information from this system is objective since firms can hardly manipulate its borrowing and payment history.

Under hypothesis1, loan rates or rates of guarantee fee have implications for how the borrower is likely to default on loans.

Hypothesis2a. Higher loan rates predict higher probability of loan defaults.

Hypothesis2b. Higher rates of guarantee fee predict higher probability of loan defaults.

In the first set of tests, I investigate how the guarantor determines the rate of guarantee fee for different borrowers. If the guarantor relies more on soft information when pricing a guarantee, soft information should play a more prominent role in estimating default probability. If there are conflicts of interest between individual guarantor officers and the whole guarantor as a firm, we should expect officer characteristics affect default probability measure. We also examine what factors affect the amount of guarantee loans. We are particularly interested to see how and to what extent the guarantor's soft information would affect final approved loan amount. Next, we explore the how the loan rates correlate to guarantor's information and loan characteristics. If banks and guarantors have the same information about borrowers, we should expect positive correlation between loan rates and the rate of guarantee fee. Next we investigate who can predict loan default correctly, guarantors or banks. I use the loan rate and the rate of guarantee fee to measure information owned by banks and guarantors, respectively. Finally, I examine the information content of loan rates and rates of guarantee fee. If guarantors make guarantee decision mainly on based on soft information it collects from borrowers, and banks determine loan rates based on hard information such as borrowers' accounting information, while loan rates are more correlated with that.

III. Data and Sample Characteristics

A. Loan Guarantee Market in China

Lending banks in developed countries usually take the certification and monitoring roles. In a few cases, the guarantor's role is played by certain government sectors. In the U.S., the Small Business Administration (SBA) acts as a guarantor on bank loans. The SBA does not make loans directly to small businesses but does help to educate and prepare the business owner to apply for a loan through a financial institution or bank. In U.K., The Small Firms Loan Guarantee (SFLG) played as the loan guarantee for small business from 1981 to January 2009. The SFLG was replaced by the Enterprise Finance Guarantee on 14 January 2009. In HK, the HKSAR Special Loan Guarantee Scheme aims to help enterprises secure loans from participating lending institutions for meeting general business needs to tide over the liquidity problem during the global financial crisis with the government acting as the guarantor.

The primary use of the guarantee programs in the U.S. or in U.K. is to make loans for longer repayment periods based in part upon looser underwriting criteria than normal commercial business loans. In contrast, the guarantee business has become a profitable but risky sector in China. Guarantors are taking over the screening job in making loans to SMEs. In China, state-owned banks usually prefer providing loans to state-owned firms, which are often very large firms, and show much less interest in small business financing. Under these circumstances, guarantors find opportunities to enter Chinese bank loan market. With expertise in investigating borrowers' business and evaluating their credit condition, guarantors can make profits by charging guarantee fee. The guarantee industry has been developing rapidly in China. By the end of year 2008, there are 4247 guarantee firms in total, providing RMB 1.75 trillion of guarantee to SMEs.

B. Sample Description

The dataset I use cover third party loan guarantee to small and medium firms in China. The dataset contains all loan guarantee issued by the guarantor from 2006 to the first half of 2009. There are 1076 loan guarantees in our final sample. It covers various industries such as manufacturing, service, wholesale, construction, etc. The majority of the borrowers are privately owned. Except for only a few cases where the loan maturity is two years, most loans in our dataset have maturity of one year.

For each loan guarantee application, the dataset contains information on its applied amount, approved amount, value of collateral, and whether the borrower defaults on its loan. The dataset is suited for my purposes for several reasons. First, it provides credit scores and a default probability measure of borrowing firms. The information helps us understand borrowers' credit condition from the guarantor's view. Second, it provides private information about the borrowers, which can not be easily obtained by other institutions. For example, it reports information such as whether the managers' relatives work for the firm, the number of shareholders, and whether these shareholders have a political background, loan history, guarantee history, etc. Studies about soft information usually use estimates from regression or other indirect proxies to measure soft information, while this dataset gives direct, easy-to-use measures. Finally, it has comprehensive accounting data of borrowers. For most borrowing firms, it provides only two consecutive years' accounting data. The available accounting period might not overlap with the guarantee application year, so our final sample reduced to 660 after including accounting data.

Table I describes the distribution of loan guarantees by year and by lending banks. The guarantor issued largest number of guarantees in 2007, with the highest default rate of 3.33%. We define a default if the borrower fails to pay in any month during the repayment period. In our sample, 16 out of 1076 loans are defined as default. The average default rate throughout 2006 to 2009 is 1.47%. According to our general knowledge of the guarantee business, the default rate is below the industry average. There are 860, or 79.93% loans issued by non-state-owned banks. The largest issuer, Shenzhen Ping An Bank, issued 454 loans, representing 42.19% of all sample loans.

Panel A of Table II reports borrower characteristics. The average total asset of borrowers is RMB 7.07 million, and the average revenue is RMB 98.60 million. Combining all available information about a borrower, the guarantor would give a default probability measure, ranging from 0 to 1. The guarantor perceives a measure below 0.4 as low risky, 0.4 to 0.6 as medium, and above 0.6 as high risky. The mean of the default probability measure is 0.497. We also examine the correlation between the rate of guarantee fee, default probability measure and accounting variables. Consistent with our expectation, higher default probability measure leads to higher rate of guarantee fee. We learnt from the correlation table that guarantor officer would give a higher score to borrowers with larger size and higher profitability, measured by ROA.

IV. Loan Pricing by Banks and Guarantors

In this section, I study how guarantors determine the rate of guarantee fee and guaranteed amount. The focus of this section is the disagreement between banks and guarantors in pricing loans.

A. Rate of Guarantee Fee and Guaranteed Amount

To explore how the guarantor determines the rate of guarantee fee for each loan, I assume the rate of guarantee fee can be presented as follows:

$$Rate\ of\ Guarantee\ Fee_i = \alpha_i + \beta_1 DPM_i + \beta_2 Firm\ Characteristics_i + \beta_3 Credit\ History_i + \beta_4 Guarantor's\ \Pr ivate\ Information_i + \beta_5 Guarantor\ Charateristics_i + \varepsilon_i \quad (1)$$

where the I subscripts indicate loan applications. DPM refers to the default probability measure of borrower i given by the guarantor. Guarantor Characteristics refers to the guarantor officer’s personal information. I deleted the observations where the guarantee fee equals to zero, since these loans are granted by governments and different in nature from other loans. The regression results are reported in table III.

In table III, the most important finding is that the rate of guarantee fee is mainly determined by the default probability measure of the borrower. As can be in the table, the coefficients of DPM are positive and statistically significant at the 1% level in all model specifications, suggesting that higher DMP leads to higher guarantee fee. On average, one percent increase of DPM would results in 33 basis points in crease in rate of guarantee fee. The coefficients of Firm Age are negative and statistically significant at 1% or 5% level, indicating that the guarantor charges lower fee from older firms. An interesting result is that the coefficients of the credit rating measure – Rating – are positive and significant, suggesting that the guarantor charge a higher guarantee fee from borrowers with a rating than those without. This result may reveal the different opinions about borrowers' credit condition held by the guarantor and rating agency.

I also explored the determinants of the guaranteed amount. The model can be expressed as follows:

$$Guaranteed\ Amount_{ii} = \alpha_i + \beta_1 DPM_i + \beta_i Applied\ Amount\ of\ Loan + \beta_2 Firm\ Characteristics_i$$
$$+ \beta_3 Credit\ History_i + \beta_4 Guarantor's\ \mathrm{Pr}ivate\ Information_i + \beta_5 Guarantor\ Charateristics_i + \varepsilon_i \quad (2)$$

The empirical results are presented in Table IV. Table IV shows that a major determinant of guaranteed amount of loan is the DPM, as indicated by the negative and significant coefficients of DPM in model 2 and model 3. These results also suggest that the final approved amount largely depends on the original amount applied for. The guarantor may increase or reduce the guaranteed amount according to DPM. 1% increase in DPM will result in RMB 6200 reduction in guaranteed amount. In contrast, the coefficient of DPM in model 1 is significantly positive, suggesting that the larger size a loan has, the higher DPM would be given by the guarantor.

B. Disagreement on Loan Pricing between Guarantor and Banks

I begin the analysis of information asymmetry between the guarantor and banks by examining how loan rates are correlated with other factors. The results are presented in

Table V. The variable in interest is DPM. Variables describing bank characteristics, loan characteristics and soft information about borrowers also enter as robustness check.

In this table, the most important results are the coefficients of DPM. The terms in parentheses below the coefficient estimates are standard errors. Throughout, we see that loan rates are negatively correlated with DPM, suggesting the guarantor and banks give different evaluation on loan risk. In practice, the guarantor scores borrowers according to accounting information, as well as by investigating the borrowing firm in person and collecting all kinds of information about competitiveness, manager ability and shareholder background, etc. Guarantors usually do not share its private information about the borrowers with banks, while banks have their own internal system recording firms' loan history. Disagreement about borrowers' risk can be partly due to different information sources guarantors and banks rely on. Besides, both guarantor officers and loan officers make guarantee or loan decisions with certain discretion (Cerqueiro et al., 2010). It is suggested in many studies that hard information, such as accounting data, can be easily manipulated by Chinese firms. Under these circumstances, it is likely that guarantors and banks have different interpretation of borrowers' information and give conflicting prediction of loan default probability.

Another result worth noting is the higher loan rates in crisis period. We define the period between July 2007 and June 2009 as the crisis period. For all specifications, the coefficients of crisis dummy are positive and significant. This finding is supported by Santos and Winton (2008), which argues that banks would be able to raise loan rates during recessions, when firms are typically in greater risk of failure, because banks have an exploitable information advantage which can lead to hold-up problem for borrowers. My result is consistent with the finding that the information hold-up effects are stronger during crisis period.

How the loan amount is associated with loan rate is also studied. Following Cerqueiro et al. (2010), which provides evidence that banks use discretion when pricing loans and the level of discretion decreases in the size of loan, I anticipate that the borrowers in my sample also face with the discretion problem. Therefore, I adopted the maximum likelihood estimation in regressing loan rates on loan size. I obtain estimates by maximizing the following log-likelihood function with respect to β and γ:

$$LogL = \frac{n}{2}\log(2\pi) - \frac{1}{2}\sum_{i=1}^{n} Z_i^{'}\gamma^{'} - \frac{1}{2}\sum_{i=1}^{n}\exp(-Z_i^{'}\gamma)(y_i - X_i^{'}\beta)^2$$

(3)

In this model, y_i is the dependent variable, X_i a vector of explanatory variables in the mean equation, and Z_i a vector of explanatory variables in the variable equation.

The positive and significant coefficients of loan size across all specifications indicate that banks charge higher interest rate to large amount borrowers. Santos and Winton (2008) provides evidence that bank-dependent borrowers, or borrowers with less access to public bond markets, are facing higher bank loan rates. It is likely that firms applying for larger amount of loan are more dependent on bank loans as financing channel. One may argue that large amount borrowers are more likely to be large in size and may find it easier to get access to public bond market, however, considering the poor development of financial markets and institutional environment in China, small firms largely depend on bank loans. The ease of access to public bond market has little effect in this case. I notice that this result is opposite to Cerqueiro et al. (2010), which concluded that the level of loan rates decrease in the size of the loan. They explain the results mainly from search costs perspective. This argument would be irrelevant for my analysis on Chinese small borrowers.

V. Prediction of Loan Defaults

The results so far demonstrate that guarantors and banks for different view in pricing loans. This section further provides evidence that loans rates have predictive power on loan defaults. Banks are found to be more effective in loan pricing.

A. Loan Rates and Prediction of Loan Default

To explore the factors that may contribute in predicting loan default, we employ the following probit regressions:

$$\begin{aligned} Default_{ii} &= \alpha_i + \beta_1 DPM_i + \beta_2 Borrower\ Characteristics_i + \beta_3 Credit\ History_i + \beta_4 Loan\ Rates_i \\ &+ \beta_5 Guarantor\ Officer\ Characteristics_i + \varepsilon_i \end{aligned} \tag{4}$$

In this specification, default is the dummy variable which takes the value of one if the loan defaults, and zero otherwise. The empirical results are presented in Table VI.

Table VI shows that the default probability measure alone does not have predictive power for loan default. In contrast, the coefficients of loan rates and *All Information,* the measure of information sharing, are significant at 5% level in all model specifications, suggesting that banks are more effective in pricing loan risks. A further interpretation is guarantors may improve their default prediction by learning information from banks. This result echoes the findings by Barth et al. (2009), who finds that private bureaus play an effective role in reducing the information gap between lenders and borrowers, and consequently corruption in lending. Guarantors' information mainly comes from its investigation of borrowers, while banks basically rely on the internal credit rating history. Intuitively, aggregating different sources of information would result in better understanding of borrowers' creditworthiness. Overall, the result strongly supports our Hypothesis2a that banks are pricing loans more effectively.

In column 2, we explore whether borrowers with a guarantee history makes a difference in default prediction. The dummy *Guaranty History* takes the value of one if the borrower was offered a loan guarantee by the same guarantor before. The coefficients across all specifications are negative and significant, indicating borrowers with a guarantee history are less likely to default. As discussed earlier, this is probability due to the increasing knowledge about the borrowers accumulated by the guarantor during previous business However, the significance is reduced with other factors entering the regression.

The age of borrowing firm is also included in the regression. The coefficient of *age* is negative and significant. Existing studies usually incorporate firm size, profitability and loan characteristics as independent variables in default prediction models, while few of them have considered firm age. Older firms tend to be large, mature firms. It is reasonable to expect that they are less like to default on loans.

B. The Role of Guarantor Officer

A worth-noting variable in Table VI is the capability measure of guarantor officers, *Low Capability*. We measure guarantor officer's capability with the number of working years by the year when a loan guarantee is processed by her. In practice, the average number of working years until promotion for a guarantor officer is 3-5 years. We regard working years longer than 8 years as an indicator of low capability. Low capability of guarantor officers is positively associated with default probability.

A number of studies provide evidence that financial intermediaries involve processing soft information[6]. Specifically, Qian et al. (2010) provides evidence that decentralization in bank system can provides stronger incentives for individual loan officers to produce soft information. Therefore, the personal characteristics of the loan officer/guarantor officer can have an effect on quality of loans granted. Focarelli and Panetta (2003) pointed out that human capital is especially important for financial services and hi-tech industries. Bellucci et al. (2010) argues that gender of loan officer and borrower can both play a role in bank-firm relationships. Bottazzi et al. (2008) provides evidence for the importance of human capital for venture capital firms. The most relevant one is Berger and Udell (2004), which finds that an easing of credit standards is resulted from the deterioration in the ability of loan officers. In our study, it is the guarantor officers that are producing a large amount of soft information, thus the ability of a guarantor officer can be associated with potential loan problems. We therefore

[6] See, for example, Diamond (1984), Ramakrishnan and Thyakor (1984), or Allen (1990).

expect the loan guarantees granted by a loan guarantor officer with lower capability are more likely to default. The results strongly support this expectation.

VI. Information Content of Loan Rates and Rate of Guarantee Fee

The results so far demonstrate that loan rates have predictive power on loan defaults. This section further explores the information content of loan rates and rates of guarantee fee. Evidence presented in this section shows that banks rely more on hard information in setting loan rates, and it is the additional part of information owned by banks than guarantors that contributes to default prediction.

A. Information Content of Rate of Guarantee Fee, Default Probability Measure and Loan Rate

I further examine the information content of loan rates, guarantee fee and default probability measure. The results are presented in table IX. The first column reveals factors affecting the price of loan guarantees. Borrowers with larger size are charged lower fee by both guarantors and banks. Regarding the possibility that the rate of guarantee fee has little variation and contains only part of information[7], I conduct a similar regression of the Default Probability Measure. It is positively correlated with leverage and negatively correlated with ROA and asset turnover. Borrowers whose manager has a political background receives lower default probability measure,

[7] I would like to thank Prof. Frank M. Song for suggestions on this point. Since the rate of guarantee fee is mainly determined by the Default Probability Measure, which is calculated by transforming the credit score given by guarantor officers, I mainly use Default Probability Measure as the guarantors' pricing of loans.

suggesting that guarantors are using some private and soft information in assessing borrower risks. Although we incorporate Guarantor's Private Information into the specifications, we should expect there are other unobservable variables affecting guarantor officers' perspective.

Determinants of loan rates are different. It is largely affected by Book Value of Shareholder Equity and Rating. Both of these two variables represent public information about borrowers. Inferring from both empirical results and discussions with guarantor officer[8], it is the guarantors that investigate borrowing firms' operation and credit condition. Banks mainly rely on public information and credit records.

It is worth noting that the coefficient of *Rating* dummy is significantly negative. The rating of borrowers is given by a third independent agency from guarantors and banks. My results suggest that firms with a rating obtain lower loan rates. As suggested by a guarantor officer that they know little about the creditability of the rating and rarely take it into consideration in setting rates of guarantee fee, it is therefore not surprising to find that the rating does not affect default probability measure given by guarantors.

B. Banks' Information Advantage

Empirical results indicate that guarantors incorporate soft information when making guarantee decisions, while banks rely more on public information and ratings. I also find evidence that it is the additional part of information banks have than guarantors that contributes to predictability of loan default. Table IX presents the results. Bank private information is the residual taken from the regression of loan rates on rates of guarantee

[8] I would like to thank Maggie Chen for useful explanations of the practical details for guarantors' daily operation.

fee. The positive coefficients of bank private information suggest that banks have more useful information in setting loan rates than guarantors. A possible explanation is that although guarantors have advantage over banks in terms of analyzing borrowers' credit risk by utilizing soft information, banks may have overwhelming advantage in collecting and analyzing hard information about borrowers. People's bank of China has been constructing an internal credit system, recording borrowers' credit history and loan performance. It is serving as an important source of information that banks rely on when determining loan amount and charge rate. Significant coefficients of loan rates suggest banks price loans more effectively.

C. A Test of Borrower Lying Behavior

As discussed in earlier in the hypothesis development in Section II, borrowers have incentives to lie about their real operation or credit condition, or hide bad information from the guarantors or banks. If bad borrowers have such incentives to lie, we would expect a predictive power of lying behavior on loan defaults. To test it, I regress book value of shareholder equity on major proxies for firm size, profitability and liquidity, and take the residual as a measure for the lying behavior. It shows in the specification as the abnormal book value of shareholder equity. The empirical results are presented in Table VIII.

Table VIII show that abnormal book value of shareholder equity is positively associated with the loan default dummy, after controlling for firm characteristics, guarantor private information and guarantor officer characteristics, and including year and industry fixed effects. This evidence provides strong support to the conjecture that borrowers have incentives to lie, and neither guarantors nor banks can detect borrowers' manipulation of financial data.

VII. Summary and Concluding Remarks

In this paper I analyze the disagreement between loan guarantors and banks in pricing loans, and the predictive power of loan rates and the rate of guarantee fee on loan default. I obtain two main results. First, guarantors and banks give conflicting default probability of loans by using different sources of information. Second, loan rates better predict loan default. The result is consistent with the predictions of the model in an asymmetric information setting.

I start the analysis by examining the pricing of loan guarantee. The rate of guarantee fee is mainly determined by the default probability measure, which is calculated by guarantor officers after investigating the borrowers' credit condition. Loans of larger size are often given higher default probability measure. Guarantee applications with higher default probability measure are more likely to see a reduction in the final approved guaranteed amount. The above analysis provides an overall picture of how a loan guarantee is processed.

My findings complement the bank lending literature, which mainly focus on banks' information advantage over other outsiders. This work is most closely related to the growing literature discussing the role of soft information used by Chinese commercial banks (Qian, Strahan and Yang (2010), Chang, Liao, Yu and Ni (2010), etc). Different from their perspective, I analyze the role of guarantors as a private bureau in alleviating information asymmetry in bank lending to small business. I focus on information conflicts between guarantors and banks. This paper also contributes to the growing literature on formal and informal finance. Ayyagari, Demirgüc-Kunt and Maksimovic (2010) question whether reputation and relationship based financing are responsible for the performance of the fastest-growing firms in developing countries. Consistent with their findings, my results have implications that informal finance is likely to be limited.

My findings have important policy implications. First, my results reveal the imperfection in information process for lending decisions. Information asymmetry among borrowers, guarantors and banks increase the borrowing cost for small business. The existence of guarantors as an intermediation facilitates the screening of loans to SMEs, but guarantors have no information advantage over banks. My findings question the contribution of soft information collected by guarantors in assessing loan risk and support the literature questioning the role of informal finance in China.

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Table I

Summary Statistics of Guaranteed Loans and Loan Defaults

This Table reports the summary of guaranteed loan characteristics by year and by lending banks. See Appendix I for variable definitions.

Panel A. Summary of Loans and Defaults

Year of Approval	No. of Loans	No. of Loan Defaults	Default Probability Measure	Loan Rate	Rate of Guarantee Fee	Default Rate
2006	247	1	0.598	6.845	1.906	0.40%
2007	359	12	0.500	7.465	1.735	3.34%
2008	310	3	0.432	7.635	1.668	0.97%
2009 H1	160	0	0.459	5.625	1.473	0.00%
Total	1076	16	0.496	7.182	1.715	1.49%

Panel B. Summary of Loans and Defaults - State-owned Bank

Year of Approval	No. of Loans	No. of Loan Defaults	Default Probability Measure	Loan Rate	Rate of Guarantee Fee	Default Rate
2006	31	0	0.581	6.834	2.032	0.00%
2007	65	3	0.519	7.823	2.029	4.62%
2008	52	1	0.438	7.803	1.962	1.92%
2009 H1	30	0	0.454	5.856	1.868	0.00%
Total	178	4	0.494	7.388	1.982	2.25%

Panel C. Summary of Loans and Defaults - Non-state-owned Bank

Year of Approval	No. of Loans	No. of Loan Defaults	Default Probability Measure	Loan Rate	Rate of Guarantee Fee	Default Rate
2006	182	1	0.600	7.072	1.890	0.55%
2007	289	8	0.494	7.369	1.669	2.77%
2008	254	2	0.431	7.586	1.624	0.79%
2009 H1	127	0	0.458	5.543	1.365	0.00%
Total	852	11	0.492	7.147	1.657	1.29%

Panel D. No. of Loans and Defaults by Banks			
Bank	**No. of Loans**	**No. of Defaults**	**Default Rate**
Industrial and Commercial Bank of China	37	0	0.00%
China Everbright Bank	4	0	0.00%
Guangdong Development Bank	29	0	0.00%
China Development Bank	5	0	0.00%
Huaxia Bank	122	3	2.46%
China Construction Bank	123	4	3.25%
Bank of Communications	31	1	3.23%
China Minsheng Bank	8	0	0.00%
Shenzhen Ping An Bank	454	6	1.32%
Shanghai Pudong Development Bank	88	1	1.14%
Shenzhen Development Bank	35	0	0.00%
Industrial Bank	64	0	0.00%
China Merchants Bank	14	0	0.00%
Bank of China	13	0	0.00%
Other Banks	46	1	2.17%
Total	1076	16	1.49%

Table II

Borrowing Firms' Characteristics and Correlation Analysis

This table reports borrowing firms' characteristics and correlation between variables. Accounting data are extracted one year before the year when a loan guarantee is approved. Firms without total asset, sales or cash data are excluded from the sample. Variables in Panel B are: (1) Default; (2) Default Probability Measure; (3) Rate of Guarantee Fee; (4) Credit Score; (5) Size; (6) Leverage; (7) ROA; (8) Asset Turnover; (9) Sales Growth. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Panel A. Borrowing Firms' Characteristics

Variable	Min	Max	Mean	StdDev	N
Total Asset	3.604	1056.700	70.969	107.787	776
Sales	0.530	1482.560	97.318	142.596	776
Leverage	0.000	0.909	0.354	0.169	776
Cash	2.000	18625.000	659.871	1448.065	776
ROA	-28.690	143.000	19.067	13.044	773
No. of Employee	10.000	3600.000	325.162	410.391	776
Asset Turnover	0.008	12.397	1.655	1.209	776
Sales Growth	-3.754	4.949	-0.005	1.482	764
Credit Score	37.000	90.000	67.777	9.072	774
Default Probability Measure	0.180	1.300	0.492	0.154	774
Rate of Guarantee Fee	0.000	4.400	1.753	0.785	776

Panel B. Correlation Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(2)	0.009							
(3)	-0.040	0.175***						
(4)	0.011	-0.459***	-0.052					
(5)	-0.033	0.071	-0.197***	-0.057				
(6)	0.026	0.143***	-0.032	-0.301***	0.252***			
(7)	0.008	-0.191	0.027	0.404***	-0.320***	-0.226***		
(8)	0.081*	-0.138***	-0.025	0.052	-0.204***	0.059	0.250***	
(9)	0.019	0.032	-0.135***	0.010	0.520***	0.186***	-0.097**	0.254***

Table III

Disagreement between Guarantor and Banks in Pricing Loans

This table reports the OLS regression results for Loan Rate. The dependent variable is Loan Rate. Loans with zero loan rates are excluded from the sample. Model 2 to 4 are estimated with fixed year and industry effect controls. Values in parentheses are standard errors. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Model1	Model2	Model3	Model4
Default Probability Measure	-1.5940	-0.7391	-1.4158	-1.3570
	(0.35)***	(0.28)***	(0.33)***	(0.33)***
State-owned Bank		0.3367	0.3526	0.3653
		(0.08)***	(0.09)***	(0.09)***
Crisis		1.2352	1.0433	0.3653
		(0.07)***	(0.08)***	(0.09)***
Borrower Characteristics				
Firm Age			-0.0025	0.0006
			(0.01)	(0.01)
Book Value of Shareholder Equity			0.0102	-0.0014
			(0.03)	(-0.05)
Value of Collateral/Amount of Loan			0.7467	0.7252
			(0.28)***	(0.28)***
Credit History				
Rating				-0.1671
				(0.08)**
Loan History				0.0307
				(0.08)
Present Loan				(-0.52)
				0.0018
Intercept	7.8830	935.181	1031.60	991.023
	(0.17)***	(85.78)***	(96.35)***	(98.30)***
Year Fixed Effect	No	Yes	Yes	Yes
Industry Fixed Effect	No	Yes	Yes	Yes
Adjusted R-square (%)	3.1	44.71	43.12	43.63
No. of Observations	610	605	439	438

Table IV
Determinants of Rate of Guarantee Fee

This table reports the OLS regression for the determinants of Rate of Guarantee Fee. The dependent variable is the Default dummy. Model 2 to 5 are estimated with year and industry fixed effect controls. Loan guarantees with zero rate of guarantee fee are excluded from the sample. Values in parentheses are standard errors. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Model1	Model2	Model3	Model4	Model5
Default Probability Measure	0.3285	0.2476	0.2360	0.2372	0.2464
	(0.06)***	(0.08)***	(0.08)***	(2.97)***	(0.08)***
Borrower Characteristics					
Firm Age		-0.0076	-0.0072	-0.0080	-0.0076
		(0.00)**	(0.00)**	(0.00)***	(0.00)**
No. of Shareholders		-0.0007	-0.0440	-0.0007	-0.0005
		(0.00)	(0.00)	(0.00)	(0.00)
Book Value of Shareholder Equity		-0.0073	-0.0111	-0.0119	-0.0112
		(0.01)	(0.01)	(0.01)	(0.01)
Value of Collateral/Amount of Loan		-0.1006	-0.0888	-0.0929	-0.0978
		(0.08)	(0.08)	(0.08)	(0.08)
Credit History					
Rating			0.0494	0.0482	0.0468
			(0.02)**	(0.02)**	(0.02)*
Previous Loan			0.0202	0.0065	0.0060
			(0.02)	(0.03)	(0.03)
Present Loan			0.0000	0.0000	0.0000
			(0.00)	(0.00)	(0.00)
Guarantor's Private Information					
Guaranty History				0.0266	0.0319
				(0.03)	(0.03)
Relatives				-0.0192	-0.0270
				(0.02)	(0.02)
Political Background				-0.0122	-0.0142
				(0.03)	(0.03)
Guarantor Characteristics					
Low Capability					0.0264
					(0.05)
Higher Diploma					0.1217
					(0.03)***
Intercept	1.8904	90.3186	98.2573	102.230	114.596
	(0.03)***	(25.55)***	(25.83)***	(26.83)***	(27.20)***
Year Fixed Effect	No	Yes	Yes	Yes	Yes
Industry Fixed Effect	No	Yes	Yes	Yes	Yes
Adjusted R-square (%)	5.13	5.08	5.49	5.33	6.80
No. of Observations	889	660	660	660	660

Table V
Determinants of Guaranteed Amount

This table reports the regression results for the determinants of guaranteed amount. The dependent variables from model 1, 2and 3 are raw guaranteed amount; the dependent variables from model 3 to 6 are: guaranteed amount scaled by total asset. Model 2, 3, 5, and 6 are estimated with year and industry fixed effect controls. Values in parentheses are standard errors. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Model1	Model2	Model3	Model4	Model5	Model6
Default Probability Measure	561.204	-72.025	-63.462	-0.0862	0.0014	0.0062
	(129.45)**	(36.05)**	(36.34)*	(0.08)	(0.02)	(0.02)
Application Amount		0.9372	0.9337		0.0001	0.0001
		(0.01)***	(0.01)***		(0.00)***	(0.00)***
Borrower Characteristics						
Firm Age		0.7167	0.7138		-0.0036	-0.0031
		(1.36)	(1.37)		(0.00)***	(0.00)***
No. of Shareholders		0.2377	0.1536		-0.0017	-0.0016
		(0.98)	(0.98)		(0.00)***	(0.00)***
Book Value of Shareholder Equity		4.8472	7.1398		0.0272	0.0264
		(4.43)	(4.53)		(0.01)***	(0.01)***
Value of Collateral		0.0054	0.0058		0.3285	0.3292
		(0.01)	(0.01)		(0.02)***	(0.02)***
Credit History						
Rating			-0.1541			0.0004
			(11.59)			(0.01)
Previous Loan			8.4489			-0.0143
			(13.66)			(0.01)*
Present Loan			-0.0000			-0.0000
			(0.00)*			(0.00)*
Guarantors' Private Information						
Guaranty History			-22.269			-0.0160
			(13.03)*			(0.01)**
Relatives			25.3150			-0.0061
			(10.94)**			(0.01)
Political Background			2.6724			0.0016
			(12.60)			(0.01)
Guarantor Characteristics						
Low Capability			40.8512			-0.0133
			(20.94)*			(0.01)
Higher Diploma			-0.0363			-0.0050
			(0.04)			(0.01)
Intercept	249.907	-4578.1	-7387.4	0.1744	5.525f6	3.2992
	(67.57)***	(11334.02)	(12080.00)	(0.04)***	(6.85)	(7.38)
Year Fixed Effect	No	Yes	Yes	No	Yes	Yes
Industry Fixed Effect	No	Yes	Yes	No	Yes	Yes
Adjusted R-square (%)	1.65	93.59	93.63	4.04	35.37	36.51
No. of Observations	1064	1057	1056	784	778	778

Table VI
Loan Rate and Loan Default

This table reports the probit regression results. The dependent variable is the Default dummy. Model 1, 2, 6, and 7 are estimated with the sample which exclude loans with zero guarantee fee or zero loan rate. Model 3 to 5 are estimated with the full sample. Included in the regressions but not shown in the table are variables indicating borrower characteristics and loan characteristics. Models are estimated with year and industry fixed effect controls. Values in parentheses are standard errors. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7
Loan Rate	0.4838					0.5660	
	(0.22)**					(0.23)**	
All Information		0.4549					0.5413
		(0.21)**					(0.23)**
Guaranty History			-0.5689			-0.4085	-0.4363
			(0.26)**			(0.43)	(0.43)
Firm Age				-0.1176		-0.1485	-0.1438
				(0.05)**		(0.07)**	(0.07)**
Low Capability					1.1041	0.8846	0.8977
					(0.33)***	(0.48)*	(0.48)*
Intercept	504.427	456.498	56.9867	13.1370	-1.5104	-33.540	-70.243
	(599.50)	(581.56)	(278.87)	(285.19)	(1.57)	(751.24)	(731.28)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower Characteristics Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
McFadden's R-square (%)	0.02	1.69	2.52	2.16	0.11	2.49	5.44
Wald Chi-square	0.78	8.07	12.76	12.13	16.44	12.00	617
Accuracy Ratio (%)	42.33	40.76	49.38	41.80	10.68	68.02	67.08
No. of Observations	612	612	770	770	770	612	612

Table VII
Loan Rate and Loan Default – Subsample Analysis

This table reports the probit regression results. Values in parentheses are standard errors. Included in the regressions but not shown in the table are variables indicating borrower characteristics and loan characteristics. Models are estimated with year and industry fixed effect controls. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

	Type of Banks				Guaranty History			
	State-owned		Non-state-owned		Yes		No	
Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Loan Rate	0.3310		0.1271		0.2020		0.4029	
	(0.15)**		(0.17)		(0.28)		(0.18)**	
All Information		0.7315		0.0624		0.2430		0.3094
		(0.34)**		(0.16)		(0.30)		(0.17)*
Intercept	578.488	808.954	429.236	424.413	305.593	309.571	405.756	381.100
	(435.61)	(1063.58)	(433.07)	(413.36)	(742.08)	(768.90)	(601.94)	(557.35)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
McFadden's R-square (%)	2.48	2.48	2.67	0.17	0.31	0.14	0.09	0.92
Wald Chi-square	4.38**	5.55	0.23	2.49	0.69	3.06	3.77**	6.07
No. of Observations	141	140	467	463	281	280	331	327
No. of Defaults	6	10	6	10	3	3	13	13

Table VIII
Information Advantage of Banks and Loan Default

This table reports the probit regression results. Bank Private Information is the residual taken from the regression of loan rate on rate of guarantee fee. Models are estimated with year and industry fixed effect controls. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Model1	Model2	Model3
Bank Private Information	0.3444	0.3643	0.5647
	(0.15)**	(0.15)**	(0.23)**
Guaranty History		0.3643	-0.3980
		(0.15)**	(0.43)
Firm Age		-0.0720	-0.1497
		(0.04)	(0.07)**
Low Capability		0.4590	0.8791
		(0.38)	(0.48)*
Size			0.1125
			(0.30)
ROA			-0.0116
			(0.02)
Leverage			0.3833
			(1.18)
Cash			1.7605
			(2.19)
Sales Growth			0.0003
			(0.16)
Asset Turnover			0.1235
			(0.11)
Log (Book Value of Shareholder Equity)			0.0291
			(0.19)
Value of Collateral/Amount of Loan			-0.9402
			(1.59)
No. of Shareholders			0.0004
			(0.03)
Intercept	593.015	312.873	-20.921
	(441.54)	(487.76)	(752.15)
Year Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
McFadden's R-square (%)	0.17	1.00	1.74
Wald Chi-square	7.82**	13.40**	13.18**
No. of Observations	612	612	612

Table IX
Information Content of Rate of Guarantee Fee and Loan Rate

This table reports the OLS regression results for rate of guarantee fee, default probability measure and loan rate. Models are estimated with year and industry fixed effect controls. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Rate of Guarantee Fee	Default Probability Measure	Loan Rate
Borrower Characteristics			
Size	-0.0590	-0.0036	-0.2660
	(0.02)***	(0.01)	(0.08)***
ROA	-0.0005	-0.0013	0.0050
	(0.00)	(0.00)***	(0.00)
Leverage	0.0062	0.0791	-0.3384
	(0.07)	(0.04)**	(0.31)
Cash	0.1030	-0.0335	0.7650
	(0.15)	(0.08)	(0.67)
Sales Growth	-0.0026	0.0031	0.0338
	(0.01)	(0.00)	(0.04)
Asset Turnover	-0.0101	-0.0110	0.0575
	(0.01)	(0.00)**	(0.04)
Firm Age	-0.0023	0.0013	0.0037
	(0.00)	(0.00)	(0.01)
No. of Shareholders	-0.0002	-0.0002	0.0028
	(0.00)	(0.00)	(0.01)
Book Value of Shareholder Equity	0.0073	-0.0055	0.1392
	(0.01)	(0.01)	(0.05)***
Value of Collateral	-0.0356	-0.0235	0.1247
	(0.03)	(0.02)	(0.13)
Credit History			
Rating	0.0103	0.0175	-0.3842
	(0.02)	(0.01)	(0.10)***
Previous Loan	0.0263	0.0000	0.1662
	(0.02)	(0.00)	(0.10)
Present Loan	-0.0000		0.0000
	(0.00)		(0.00)
Guarantor's Private Information			
Guaranty History		-0.0042	
		(0.01)	
Relatives		-0.0009	
		(0.01)	
Political Background		-0.0236	
		(0.01)**	
Intercept	2.4822	0.5224	8.4806
	(0.14)***	(0.07)***	(0.62)***
Adjusted R-square (%)	7.82**	13.40**	13.18**
No. of Observations	612	612	612
Whether the Residual can Predict Default?	No	No	Yes

Table X
Can Abnormal Book Value of Shareholder Equity Predict Loan Default?

This table reports the OLS regression results showing the predictive power of abnormal book value of shareholder equity. The Dependent variable is the Default dummy. Abnormal Book Value of Shareholder Equity is the residual taken from the regression of raw Book Value of Shareholder on hard information measures (ROA, Sales, leverage Cash, Asset Turnover and Sales Growth Rate). Models are estimated with year and industry fixed effect controls. See Appendix I for variable definitions. ***, **, and * mean significant at the 1%, 5%, and 10% level, respectively.

Variable	Model1	Model2	Model3
Abnormal Book Value of Shareholder Equity	0.4938	0.5926	0.6792
	(0.25)***	(0.26)**	(0.31)**
Loan History		-0.7945	-1.0961
		(0.34)**	(0.47)**
Firm Age		-0.1543	-0.1771
		(0.06)**	(0.07)**
Low capability		0.9577	1.0334
		(0.44)**	(0.48)**
Political Background			0.6639
			(0.34)*
Relatives			-0.2516
			(0.36)
Value of Collateral/Amount of Loan			-1.4114
			(2.18)
No. of Shareholders			-0.0328
			(0.07)
State-owned Bank			0.3600
			(0.36)
Intercept	-2.2398	-1.2046	-1.1883
	(0.13)***	(0.32)***	(0.45)***
Year Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
Wald Chi-square	3.82*	15.62***	17.53*
Observations	658	657	624

Figure1. Guaranty Fee and Default Probability Measure

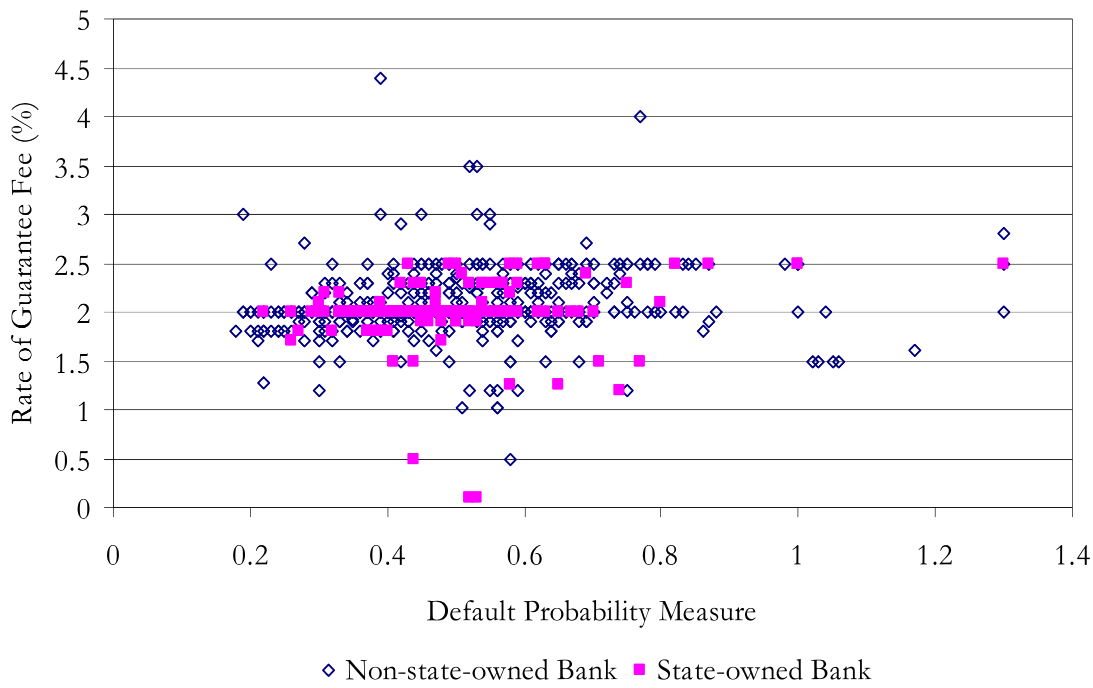


Figure2. Loan Rate and Guaranty Fee

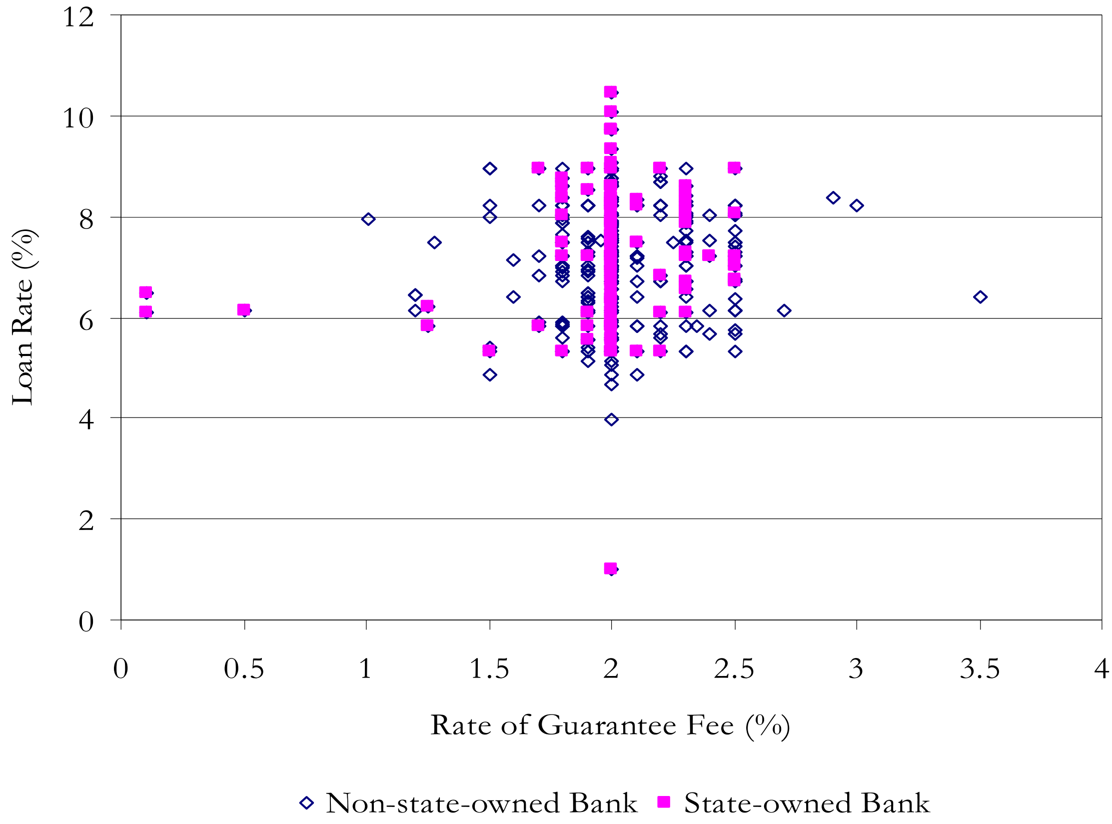


Figure3. Loan Rate and Default Probability Measure

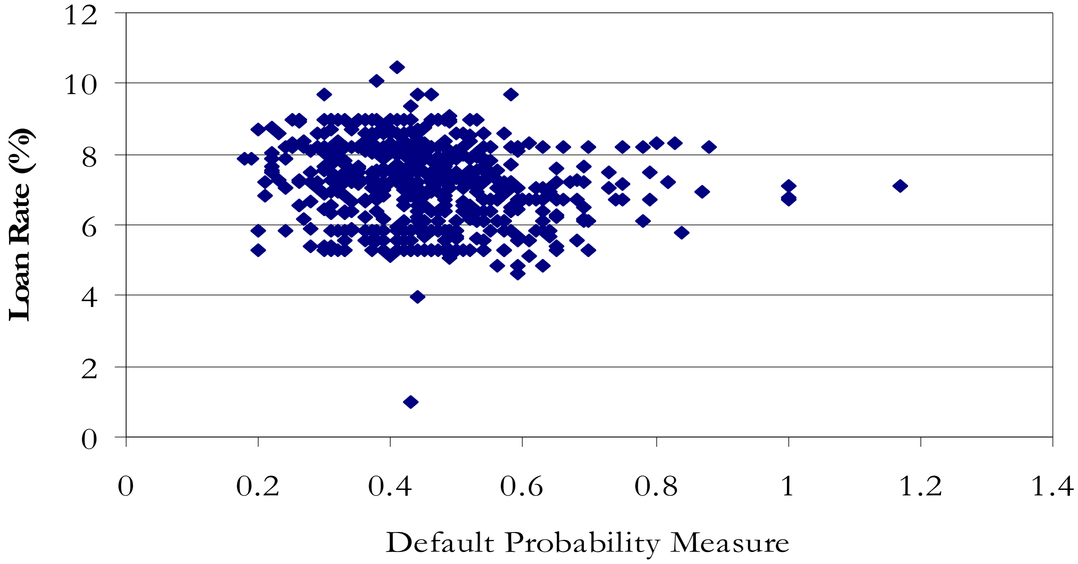
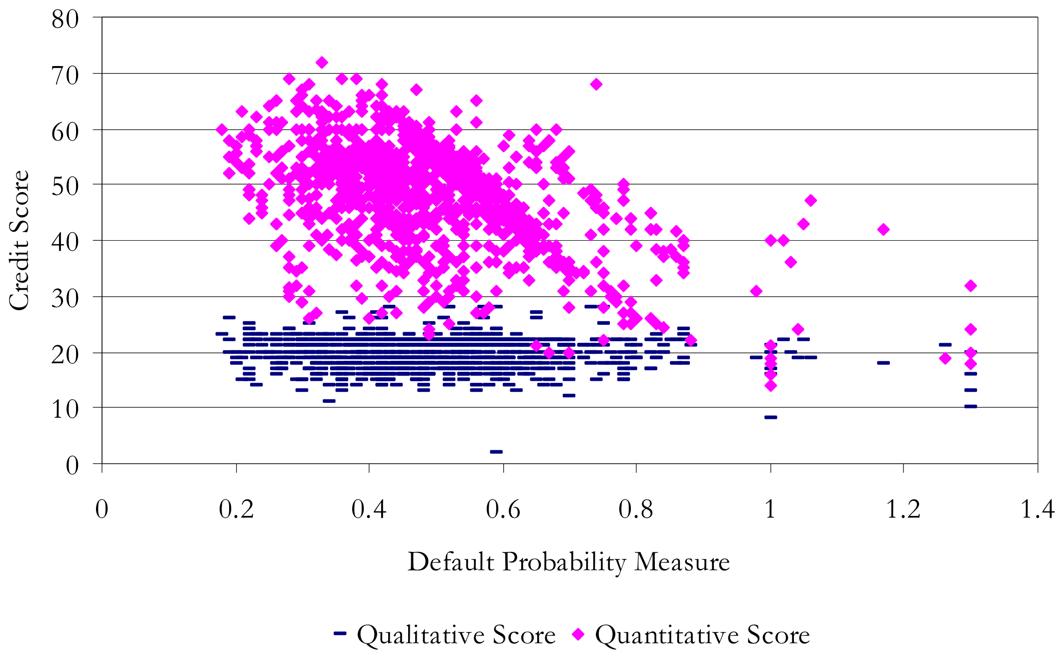


Figure4. Credit Score and Default Probability Measure



Appendix I
Variable Definitions

Variables	Definition	Measure as of Year
Default	A dummy variable that equals one if a firm defaults on its short-term loans, and equals zero otherwise. Default occurs if a firm fails to repay any of the installments.	This variable is measured within one year or two years after the loan is originated.
Default Probability Measure	Guarantee firm's internal credit risk measure. The score is between 0 and 1. The higher the score is, the riskier the short-term loan is.	
Guaranty History	A dummy variable that equals to one if a firm was guaranteed by the same guarantor before, and equals to zero if not.	
Loan History	A dummy variable that equals to one if a firm was granted loans before, and equals to zero if not.	
No. of Loans	The number of loans the borrowing firm has already had until the application of the new loan.	
Rate of Guarantee Fee	Percentage rate of credit guarantee fee charged by the guarantee firm.	
Qualitative Score	A score given by the guarantee firm. The calculation is based on the borrower's qualitative variables (The manager's ability, the firm's reputation, etc).	
Quantitative Score	A score given by the guarantee firm. The Calculation is based on the borrower's quantitative variables (The firm's profitability, sales, etc).	
Credit Score	The sum of qualitative score and quantitative score.	
Firm Age	No. of years from the date of foundation of a borrowing firm to its date of loan application.	
Size	The natural log of book value of total assets at the end of the year.	
Leverage	Financial leverage, calculated as total liabilities divided by total assets at the end of the year.	These variables are measured at one year before the year when the loan was approved.
ROA	Return on assets, calculated as net income divided by total assets.	
Asset Turnover	Asset turnover ratio, calculated as total sales divided by total assets.	
Sales Growth	The natural log of the division of sales of current year by that of previous year.	

Relatives	A dummy variable that equals one if the borrowing firm's manager's relatives are working in the firm, and equals to zero if not.	
Political Background	A dummy variable that equals one if the borrowing firm's manager has political background, and equals zero if not.	
Low capacity	A dummy variable that equals one if the project manager in the guarantee firm had worked for 8 years or more at the year of loan application he/she was in charge of.	This variable is measured at the year when the loan was approved.
Higher Degree	A dummy variable that equals one if the project manager in the gurantee firm has master's or doctor's degree.	
State-owned Bank	A dummy variable that equals one if the loan-issuing bank is state-owned, and equals zero if not.	
Crisis	A dummy variable that equals one if the loan was approved between July 2007 and June 2009, and equals zero if the loan was approved before July 2007.	
Application Amount	The amount of the loan guarantees that the borrower applied for to a guarantor.	