The Impact of Organizational and Incentive Structures on Information Production: Evidence from Bank Lending[*]

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Abstract

In 2002 and 2003, many Chinese banks implemented policy reforms that delegated lending decisions and increased the accountability to individual decision makers. The policy change followed China's entrance into the WTO and offers a plausibly exogenous shock to loan officer incentives to produce information on borrowers. Using detailed loan-level data from a large, state-owned bank, we find that an internal borrower-risk assessments ('soft' information) have a more pronounced effect, relative to publicly available information ('hard' information), on both price and non-price terms of loan contracts *after* the reform. When the loan approval decision is made at the branch above which the risk assessment is made, the use of soft information declines. Our results highlight how organizational structure and incentives can affect information production, and in particular, the quality of soft information.

JEL Classifications: G2, L2, D8.

Keywords: Soft information, bank loan, interest rate, default, hierarchy.

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Abstract

In 2002 and 2003, many Chinese banks implemented policy reforms that delegated lending decisions and increased the accountability to individual decision makers. The policy change followed China's entrance into the WTO and offers a plausibly exogenous shock to loan officer incentives to produce information on borrowers. Using detailed loan-level data from a large, state-owned bank, we find that an internal borrower-risk assessments ('soft' information) have a more pronounced effect, relative to publicly available information ('hard' information), on both price and non-price terms of loan contracts *after* the reform. When the loan approval decision is made at the branch above which the risk assessment is made, the use of soft information declines. Our results highlight how organizational structure and incentives can affect information production, and in particular, the quality of soft information.

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I. Introduction

There are at least two types of information that are essential in communications and business transactions: 'hard' information that is publicly verifiable (e.g., by a court), and 'soft' information that is *not* verifiable and may or may not be publicly observable (e.g., Stein, 2002). A growing literature emphasizes the importance of soft information for transactions such as financial contracts, and demonstrates that organizational structure can affect how this type of information is produced and used. In this paper, we examine how banks with different organizational and incentive structures produce and process soft information in setting both price and non-price terms of loan contracts, and how that information correlates with loan outcomes.

We use data from China, where the banking sector has historically been dominated by large, inefficient state-owned banks relying on centralized decision-making processes. Following China's entrance to the World Trade Organization (WTO) in December 2001, however, many banks, and in particular, state-owned banks, implemented a series of reforms during the second half of 2002 and throughout 2003 with the focus on *decentralization*—shifting the responsibilities of making lending decisions from committees to individual officers working in branches that process loan applications.[1] These reforms provide stronger incentives for individual loan officers to produce soft information, yet they are plausibly exogenous from the perspective of loan officers because the reform decisions came from the highest level due to external pressure.

To test how a shift in incentives affects contracting, we exploit detailed proprietary loan-level data from a large, nationwide state-owned bank that provides us both contract terms (interest rates and credit limits) and outcomes (default). We extend the literature by testing how incentives to produce soft information affect, first, how banks use that information in setting ex ante terms and,

[1] The four largest state-owned banks have become publicly listed and traded companies in both domestic and Hong Kong exchanges, with various agencies of the government retaining majority (equity) control. These banks have not been severely affected by the 2007-2009 global financial crisis, and are currently among the largest banks in the world (source: *Bloomberg*). See, e.g., Allen, Qian, Zhang and Zhao (2010) for more details.

second, how well that information forecasts loan performance. We also test how organizational distance between the producer of soft information and final decision maker affects production of soft information.

Our loan sample covers borrowers with various ownership types located in more than twenty cities across China for the period 1999-2006. We treat loans originated in the first half of 2002 and earlier (2004 and later) as the pre-reform (post-reform) period. For dependent variables, we include a pricing variable on loans (interest rate) and a non-price variable (the credit limit, or size of the loan), as well as the outcome of the loan (whether it defaults or not). The key explanatory variable, and our proxy for soft information, is the *internal* risk measure of the borrower—it varies from one to eight, with a higher score indicating a borrower with *higher* credit quality. Before reform these *subjective* ratings were collectively produced and signed off by a group of loan officers from the bank's loan investigation unit; after reform, however, *individual* loan officers within the unit became responsible for the ratings and can be held liable for bad loans extended based on inaccurate or biased ratings.

In our basic models, we examine and compare the impact of this internal rating variable on loan contract terms and performance during the pre- and post-reform periods by interacting the rating with a post-reform dummy. As control variables we include firm location, bank branch and year fixed effects, as well as measures of hard information of the borrowers—firm size, return on assets (ROA) and leverage. For both the pre- and post-reform periods, we also regress the internal ratings on hard information variables, allowing us to decompose ratings into two parts: the predicted value measures how all the hard information is incorporated in ratings, whereas the residual is a more direct measure of soft information.

We draw two broad conclusions. First, decentralization that holds individuals accountable strengthens incentives to produce high-quality soft information. Interestingly, we find that the internal ratings become tougher *after* the reform—there are more loans (with similar characteristics based on *hard* information) that received the two lowest possible ratings. This shift in ratings is consistent with ratings 'inflation' or 'softness' during the pre-reform period, and is also consistent with loan officers' tendency to assign lower ratings when they are responsible for defaulted loans after the reform. More importantly, the rating has a stronger effect, relative to publicly available information (hard information), on both the price and non-price loan terms *after* the reform. Specifically, a better rating leads to a greater reduction in interest rates and greater increase in loan size in the post-reform period than in the pre-reform period. In fact, we find no effect of the internal rating on loan terms prior to the reform. When we include both the predicted value (hard information component) and the residual of ratings as regressors, we find that the impact of the predicted value on loan terms actually drops post-reform, while the impact of the residual increases. These findings indicate that better incentives lead to better quality soft information, which in turn enables the lender to rely less on hard information (and more on soft information) to price loans and set credit limits.

Given that interest rates are partially controlled in China in that the central bank sets the upper and lower bounds on interest rates on loans (and deposits), it makes sense that we also find soft information plays a greater role in setting credit limit (loan size) in addition to interest rates. Lenders use multiple contracting dimensions that go beyond the interest rate to solve control problems and to mitigate risk. This finding confirms the importance of examining both price and non-price terms of the contracts, especially in environments where interest rate is not fully effective in pricing risk (e.g., Stiglitz and Weiss, 1981; Qian and Strahan, 2007). Finally, we find some evidence that internal ratings become a better predictor of loan default after the reform. Overall, with better incentives banks produce higher quality information, and this information is used more prominently and effectively during contracting.

In our second set of tests, we consider how increasing organizational distance affects the use of information.[2] To measure organizational (or hierarchical) distance, we build an indicator that equals one if management making final loan approval decisions resides in branches *above* those in which internal credit ratings have been generated (i.e. the branch where the borrower interacts with the banker). As in Stein (2002), we posit that if the loan officers creating the rating knows that instead of senior officers from their own branch, with whom they can communicate on a daily basis, someone from another branch (above theirs in terms of hierarchy) is in charge of loan approvals, their incentive to produce high-quality rating will decrease. We find that the weight placed on the internal ratings declines when hierarchical distance increases; *and* in these cases the ratings become poorer indicators of loan default (although this result is weaker statistically).

Our paper contributes to and extends the literature on soft information in financial contracting. Despite ample theoretical work in information transmission, and in particular, understanding how organizational structure and complexity affects the production and use of soft information (e.g., Crawford and Sobel, 1982; Radner, 1993; Bolton and Dewatripont, 1994; Aghion and Tirole, 1997; Garicano, 2000), there is only limited empirical validation of these theories. A major obstacle is data on soft information as well as how hierarchical structures can be converted into quantitative variables from within and across firms. An additional difficulty is to find plausibly exogenous variations across firms in these structures. In these regards, our results based on exogenous shocks to the banking sector and detailed loan-level data provide direct evidence that highlight the importance of the design of organizational and incentive structures within firms for the production of soft information. Better information, in turn, expands the supply of credit and improves (lending) outcomes.

[2] We also include the number of kilometers between the headquarters of the borrower and the *nearest* branch (of any lending institution in the area) to measure geographical distance, and find it also has a negative impact on soft information. However, the impact is not statistically significant (and not reported in tables) in part due to extensive branching throughout the countries by all major Chinese banks.

Our results are of particular relevance for emerging economies that aim to develop their financial institutions. Given the ‘populist’ demand for tighter regulations on financial institutions following the 2007-2009 global financial crisis, our results also call for more caution in excessive regulations (in any country) as they may destroy the incentive structure to produce high-quality soft information, which is central in financial contracting and most business transactions.

There are a few recent empirical studies in banking that exploit how variations in size or organization complexity affect soft information production and usage, but they are unable to exploit plausibly exogenous variations such as the policy innovation in China as in our context. For example, Berger et al (2005) compare the use of soft information for large versus small U.S. banks, finding that smaller organizations seem better able to provide incentive for investment in soft information. Liberti and Mian (2010) use data from one bank in Argentina to explore how hierarchies within banks affect the use of soft information in determining credit limits. Their identification strategy relies on the bank’s use of a well-defined set of rules to assign different hierarchical distances, which allows the authors to control for these observable borrower characteristics. Our study extends their findings in several directions. First, we are able to exploit an exogenous shock whereby the incentive of loan officers to collect soft information increases. Second, we explore not only credit limits but also loan pricing and outcomes. In addition, Chang et al. (2010) also use information from one bank in China and find that soft information predicts loan defaults, especially when the bank has a long-term relationship with borrowers. Once again, our work differs from theirs in that we identify an exogenous shock to the incentive in providing soft information. We also look at whether enhanced incentive improves the predictability of soft information on loan defaults. We find that the impact of the enhanced role of soft information in the lending process, as a result of the reform, works mostly through better setting *ex ante* loan contract terms and control borrower risk, thus likely expanding credit supply to risky borrowers but not necessarily lowering default rates. Finally, other papers find physical distance between lenders and borrowers adversely affects the quality of soft information (e.g., Petersen and Rajan, 2002; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). What we show is that hierarchical, or organizational distance, can also reduce the incentive to produce soft information. This makes the reform of organizational structures a top priority (along with bank branching) for developing financial institutions in emerging economies.[3]

The rest of the paper is organized as follows. In Section II, we describe China's banking sector and the policy reforms that we exploit as our main identification strategy. We also review related strands of literature on the production and use of soft information. In Section III, we describe our sample of bank loans, and then present the empirical tests, results and discussions. Section IV concludes the paper. The Appendix contains case studies on how internal credit ratings (containing soft information) are created.

II. Institutional Environment, Organization Structure, and Lending Process

In this section we first describe China's banking sector, including the organization structure and lending process of state-owned banks and the regulatory environment. We then describe the policy change as a result of China's entrance to WTO in 2001. We also briefly review related strands of literature on information transmissions, organizational structure and financial contracting.

II.1 Overview of China's Banking Sector and Lending Process

The large banking system has played an important role in financing the growth of China's economy, now the second largest in the world (Allen, Qian and Qian, 2005). The four largest, state-owned commercial banks have nation-wide networks of branches and control the majority of assets

[3] In addition, Mian (2006) shows that domestic banks tend to invest more in relationship, while Liberti (2004) exploits a change in incentives with a bank, finding that effort by lending officers to invest in soft information increases.

in the banking system, although their dominant status has been weakened in recent years with the entrance and growth of many domestic and foreign banks and non-bank financial institutions. The most glaring problem of the banking sector had been the high levels of non-performing loans (NPLs), most of which accumulated in the ‘Big Four’ state-owned banks from poor lending decisions to state-owned enterprises (SOEs). Following the Asian Financial Crisis in 1997, China’s financial sector reform began to focus on state-owned banks, with the goal of improving their efficiency—i.e., to make these banks behave more like profit-maximizing commercial banks and lowering the level of NPLs. With the help of sustained economic growth, the government’s concerted effort during the past decade have paid off, as the level of NPLs has been steadily decreasing after reaching its peak during 2000-2001. All of the Big Four banks have become publicly listed and traded companies (in both domestic and Hong Kong exchanges) in recent years, with the government and its various agencies retaining majority control (through the holding of large equity blocks). With prudent investment approaches, these banks have not been severely affected by the 2007-2009 global financial crisis, and are currently among the largest banks (both in terms of market capitalization and assets) in the world.

China’s banking sector, as other sectors of ‘strategic importance,’ has been under intensive monitoring by the government, mainly through its central bank (People’s Bank of China, or PBOC). The PBOC limits the movements of interest rates on both deposits and loans by setting base rates along with upper and lower bounds, and these rates and bounds vary over business cycles and loan maturities. Figure 1 shows the movements of (regulated) interest rates during our sample period. Within the specified bounds, however, the lenders (and borrowers) can freely choose to set interest rates. In our empirical tests on the pricing of bank loans, we use a standardized rate that is between 0 (actual rate equals the lower bound) and 1 (actual rate equals the upper bound) and we also include year fixed effects. Since interest rates can only vary within bounds and hence the *ex ante* pricing tool for the banks in controlling borrower risk is limited, it is important to also look at non-price terms of the loan contracts; hence we also focus on loan size.[4]

China's entry into the WTO in December 2001 marked the beginning of its integration into global markets and economies—all member countries of WTO must (eventually) open up domestic markets and allow frequent and large-scale capital flows.[5] In anticipation of much more competition from foreign (and domestic) financial institutions, many Chinese banks, especially those that are ultimately owned by the government, began implementing a series of reforms during the second half of 2002. These reforms were not triggered by any specific problem of any major bank; rather, the decisions to reform were made at the highest level in order to improve the competitiveness of all large state-owned banks against pending foreign competition. Therefore, in our view these reforms provide plausibly exogenous shocks to the banking sector, particularly from the view of the loan officers at different branches across the country.

One of the central themes in this round of reforms is decentralization—imposing greater responsibilities on individual loan officers in charge of different stages of lending. Under the old regime, the entire lending process, from loan application and the initial screening of borrowers to the final approval of the terms of loan contracts, was done within the same branch by possibly the same group of employees (and signed off by the president of the branch) without any clear designation of individual responsibilities. Since the 'group' is responsible for every step of the lending process, individual officers lacked the incentive to perform their tasks. Under the new

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[4] We do not consider loan maturities as a dependent variable. Given the uncertainty in how the government sets and changes upper and lower bounds on interest rates, most of the loans in our sample have a maturity less than one year. Moreover, since the bounds on interest rates vary with loan maturities, it is unclear whether loan maturity is an independently chosen contract term.

[5] The growth of financial institutions outside the Big Four banks is visible in the data. For example, in 2001, the total assets, deposits, and loans made of all "other commercial banks," where various joined ownerships are forged among investors and local governments, and foreign banks, are about a quarter of those of the Big Four banks; in 2008, the scale of these institutions in the same categories is more than half of the Big Four banks. See, e.g., Allen, Qian, Zhang and Zhao (2010), and the *Almanac of China's Finance and Banking* (2000-2008), for more details.

regime, there are up to five subgroups/divisions within a branch, each with clearly defined functions/roles during the lending process: (initial) investigation, verification, deliberation and discussion, approval, and post-loan monitoring and management. Individual officers must sign off on the reports produced along each step of the process. In particular, loan officers are responsible for the internal ratings and can be held liable for bad loans extended based on inaccurate ratings.

While the delegation of important steps and tasks to individual employees aims to enhance their incentives to exert efforts and improve the accuracy and efficiency of the lending process, the approval of the final terms of the loan contract is left with a committee (through voting) consisting of senior officials of the branch, with at least one official *not* involved with any of the earlier stages of the lending process. The reason for this approach is to avoid granting excessive power to one or a few individual officers, which could induce corruption and other bad behaviors. In some cases, the final decision on the terms of loans is made by officials at a branch *above* the one where the previous steps of the lending process have been carried out.

Internal documents from the bank and discussions with senior bank officials reveal that whether the approval decision is shifted upward along the hierarchy chain is predetermined. In general, these decisions are based on three factors. First, if the bank branch that receives loan applications and produces internal ratings has poor prior performance, their decision power may be taken away. Second, if the bank branch is located in a region that has struggled economically, which makes all the borrowers riskier than those from other regions, the decision-making may shift upwards. Finally, if a borrower itself is deemed 'risky,' either because it has a poor prior record in repaying loans and/or has subpar recent performance, the final decision to lend to the borrower may come from a higher ranked branch. In our empirical tests we explicitly examine which loans are more likely to go up the branching chain and the impact of this hierarchy decision process on the production of soft information.

Once a loan is made, the bank/lender enters the post-loan management phase and actively monitors the borrower and continues to reassess the (repayment) risk. If a firm defaults on the loan—failure to pay the interests and/or principal amount on time, the bank typically (privately) works out a loan/debt restructuring plan with the firm. The bank can also take a number of other actions, including repossessing collateralized assets, asking the guarantor(s) (individuals, firms, or other entities) of the loan to repay, or taking the firm to court. In some cases involving a defaulted state-owned firm/borrower, the government may step in and (partially) repay the bank. In our empirical tests we distinguish borrowers' ownership types—i.e., whether it is ultimately owned by the state or not.[6]

II.2 Theoretical Background and Hypotheses on Soft Information and Contracting

It is well known that both 'hard' information and 'soft' information are important for information transmission and communications. The non-verifiability of soft information, and different (and possibly unknown) incentives of agents producing and transmitting this type of information (see the seminal work of Crawford and Sobel, 1982, among others), makes it more intriguing and potentially the determining factor in the success of communications and business transactions. Theoretical work has examined two related aspects of how organizational structures and incentives affect the production and quality of soft information (see. e.g., Petersen, 2004, for a review). First, individuals with more authority and responsibilities have a stronger incentive to produce soft information so as to put their own stamp in the decision process (e.g., Aghion and

[6] China enacted a new bankruptcy law in August 2006 (effective on June 1, 2007), which applies to all enterprises except partnerships and sole proprietorships. In many aspects the new law resembles bankruptcy laws in developed countries such as the UK. For example, it introduces the (independent) bankruptcy administrator, who manages the assets of the debtor after the court has accepted the bankruptcy filing. Despite all the legal procedures specified by the law, enforcement of the law remains weak and inconsistent. Many distressed and insolvent firms are kept afloat, and almost all the listed firms that file bankruptcy end up with restructuring plans and are rarely delisted.

Tirole, 1997). Second, large hierarchical organizational structures, while providing advantages such as specialization and parallel processing, reduce ex ante incentives of individuals to produce soft information (e.g., Stein, 2002) and impose higher ex post communication costs across different hierarchy levels (e.g., Radner, 1993; Bolton and Dewatripont, 1994; Garicano, 2000).

Testing these theories has been challenging, because data on soft information are difficult to observe and because hierarchical structures are often difficult to convert into quantitative variables. In addition, finding plausibly exogenous variations across firms in organizational and incentive structures is a necessary condition to draw clear inferences. With the exogenous shock to the organizational structure of the same bank (with nationwide branches) described above and detailed loan-level data, we can test how different structures within firms affect the production and quality of soft information.

In our first set of tests, we examine how soft information affects the terms of loan contracts. If individual loan officers have a stronger incentive to produce soft information after the reform, soft information should play a more prominent role in setting contract terms relative to hard information on the borrowers (size, ROA, leverage, etc) and the loan (purpose and type). As the effectiveness of using interest rates to price and control risk is limited in environments of asymmetric information and weak enforcement (e.g., Stiglitz and Weiss, 1981; Diamond, 2004; Qian and Strahan, 2007), it is important to also examine nonpricing terms of the contracts. More specifically, the improvement in internal ratings (of the same unit) should lead to a greater increase in loan size and greater decrease in interest rates in the post-reform period. These results would provide the ex ante quality measure of the soft information. We also examine how effective can the soft information predict loan outcome (defaulted or not) after controlling for hard information. This would serve as the ex post quality measure.

III. Data, Empirical Methods and Results

III.1 Data and Key Variables

Our proprietary data come from a large bank that is ultimately owned by the state and has a nationwide network of branches that handle deposits and loan applications. The bank provides us with a large sample of loans with borrower firms coming from twenty-four cities of different sizes, located in all the regions of China, including the developed coastal area, the northeastern (traditional) industrial base, and less developed inland regions. There are small bank branches in the sample located in rural counties, and large branches located in provincial capitals, as well as branches in between. We include city fixed effects in all of our tests.

We include a variety of measures of hard information and use the bank's internal credit rating to measure soft information. Hard information measures include information that is externally verifiable, such as borrower asset size, return on assets, leverage, industry, and location, as well loan type and purpose. Our measure of soft information is the loan officer's subjective rating of the borrower, which ranges from one to eight, where eight represents borrowers with the lowest default risk (and highest credit quality). As described above, prior to the reform (first half of 2002 and earlier), individual officers who produced the ratings did not need to sign off on the ratings report; rather, this report and all the subsequent reports related to the verification and approval of the loan are signed by the same executive(s) of the branch. However, after the reform (2004 and later), individual officers must sign the ratings report and bear personal responsibilities of the quality of the report.

Based on internal documents and discussions with bank officials at different levels, we know that the production of soft information is based on the loan officers' evaluation of the (borrower) firm's recent and past performance, both in terms of its own profitability and records in repaying loans in the past, as well as its projected growth/performance during the loan period. The evaluation process also includes discussions with borrower firms' executives, potential guarantors, business partners and customers, and local government officials who may have a vested interest in the firm. Clearly, this process includes the usage of both hard and soft information, possibly altered by the personal interests of the officers when the report is produced. In Appendix A we provide two case studies on how the subjective ratings are created and what types of soft information (not verifiable by a third part) are included. These case studies also show that not all soft information is accurate, leading to different quality (of these ratings) in predicting the outcome of the loans.

Panel A of Figure 2 reports two histograms of the actual distributions of the soft-information score during the pre-reform (pre-2003) and post-reform (post-2003) periods. At first blush it appears that the distribution shifted quite dramatically over time toward riskier borrowers (also see Panel A, Table 1). For example, during the pre-reform years almost no borrowers received ratings in the lowest two categories, whereas 12% received ratings in the highest category. Post-reform we see almost no mass in the highest ratings bin, but more than 13% receive scores in the lowest two bins. Making loan officers more accountable for credit ratings may change both the information content of credit ratings *and* shift the distribution of ratings. For example, risk-averse loan officers may be less willing to grant the highest scores if they may be later held accountable for borrower defaults. Increased lender conservatism could thus shift the distribution of scores to the left even if average borrower risk has not changed.[7] Better information content, in turn, implies that the bank will place more weight on the credit score in setting loan terms, which we explore below.

To test for loan-officer conservatism, we estimate a predictive model from the post-reform sample, and then compare the actual vs. predicted credit scores from that model using borrower characteristics in the pre-reform sample. That is, we first regress the actual credit scores in the post-

[7] Agarwal and Wang (2009) use data from small business loan officer compensation from a major commercial bank and find that incentive-based compensation (without much downside penalties) increases loan origination and induce the loan officers to book more risky loans.

reform sample on borrower observables (i.e., hard information). The model includes the log of borrower assets, leverage, return on assets, the log of the minimum distance to the nearest potential lender, and indicators for state-owned enterprises, private enterprises, industry and city. We then apply the estimated coefficients from this model to the pre-reform data to build a hypothetical credit scores (e.g. predicted values) that would be observed if loan-officers behaved pre-reform as they had behaved post-reform.

Panel B, Figure 2 reports the distribution of these hypothetical credit scores and compares it with the actual distribution during the pre-reform period. Clearly, the mass shifts sharply to the left. For example, borrowers that actually received scores in the 7-8 range would likely have gotten scores 1 to 2 notches lower if they had applied during the tougher, post-reform regime. Overall, the mean of the hypothetical score is 1.5 notches lower than the actual scores (falling from 5.6 to 4.1). Thus, the reform increased loan-officer toughness. In the next sections we test whether this toughness also improved the value of the credit scores for making lending decisions.

III.2 Empirical Strategy

Our main empirical strategy tests whether links between the bank's soft-information credit score to the loan interest rate, the credit limit (log of loan size), and the loan default outcome increase when: 1) individual responsibility for production of soft information increases; and, 2) the organizational distance from the loan officer (who produces soft information) and decision-maker on loans (at the same branch of the loan officer or at a higher branch) decreases. As discussed earlier, the changes in individual responsibilities occurred in 2003 in response to increasing pressure on state-owned banks to adopt best practice after China entered the WTO. This change is plausibly exogenous from the perspective of the loan-officers engaged in information production and contracting with borrowers. For distance, we build two distinct measures. The first one is the geographical distance between the borrower and the *nearest* branch of all lending institutions in the area, rather than the distance to the actual branch of our bank. This variable does not depend on the borrower's choice of which bank to approach for credit, hence side-stepping the endogenous matching between borrowers and lenders. From Table 1, the average minimum distance between a borrower firm and a lending institution is only 2.16 km during the post-reform period (2.93 km during the pre-reform period), reflecting all major Chinese banks' extensive branching efforts. While we do find a negative impact of physical distance on the production and use of soft information, the impact is generally not statistically significant. In empirical tests below we do not report this physical distance variable to save space.

The other distance measure is based on within-bank *organizational* (or hierarchical) distance between the employees interacting with the borrower and employee vested with decision rights over the loan. Specifically, we create an indicator variable equal to zero if the loan approval is done in the same branch office where the lending officer responsible for constructing the soft-information credit score works. We estimate a specification with the two distance measures together. Since our measure of hierarchical distance is only available after 2002, we report this third specification without the policy reform interaction. In these regressions, we do not have an exogenous measure for the hierarchical distance. However, we do condition on all of the variables associated with the bank's decision on which layer of the hierarchy approves or denies the application.

To examine the impact of soft information on loan terms and outcome, we build two sets of models. In the first (unconstrained model), we use the internal rating scores (1 to 8, higher is better credit quality) while controlling for hard information variables and fixed effects. As discussed earlier, we interact a post-reform indicator with the score to examine differential effects of the rating on loan terms and outcomes during the two periods; we also interact the hierarchy indicator with the rating to examine whether organizational distance attenuates the impact of soft information on loan terms and in predicting outcomes.

In the second approach (constrained model), we first regress the internal ratings on the hard information variables in both the pre- and post-reform periods and obtain both the predicted rating and the residual rating for each loan (Table 2). The advantage of this approach is that the predicted value collapses the hard information about the borrower into a single dimension, which allows us to compare the weights the bank places on hard information versus soft information in setting loan terms in both the pre and post-reform periods. In the second stage, we therefore include both the predicted and residual ratings (and fixed effects) and interact both variables with the post-reform indicator. This will allow us to examine possibly different effects of how both hard and soft information determine loan terms and outcomes before and after the reform. Finally, we interact the hierarchy indicator with both the predicted and residual values to see how hard and soft information is processed when the final decision on loans is made at a higher level branch.

To summarize this description of our models analytically, here are the three sets of regressions that we estimate:

$$\begin{aligned}&\textit{Loan term (or outcome)}_{i,t} = \beta^1 \textit{Rating}_{i,t} + \beta^2 \textit{Rating}_{i,t} \times \textit{Post-2003}_t + \textit{Fixed effects}\\&\qquad + \textit{Hard-information controls}_{i,t} \textit{ and interactions} + \varepsilon_{i,t},\\&\qquad\qquad t = \textit{1999-2006 (second half of 2002 and 2003 omitted)}\end{aligned} \tag{1}$$

$$\begin{aligned}&\textit{Loan term (or outcome)}_{i,t} = \beta^1 \textit{Predicted Rating}_{i,t} + \beta^2 \textit{Residual Rating}_{i,t} + \beta^3 \textit{Predicted}\\&\qquad \textit{Rating}_{i,t} \times \textit{Post-2003}_t + \beta^4 \textit{Residual Rating}_{i,t} \times \textit{Post-2003}_t + \textit{Fixed effects} + \varepsilon_{i,t},\\&\qquad\qquad t = \textit{1999-2006 (second half of 2002 and 2003 omitted)}\end{aligned} \tag{2}$$

$$\begin{aligned}&\textit{Loan term (or outcome)}_{i,t} = \beta^1 \textit{Rating}_{i,t} + \beta^3 \textit{Rating}_{i,t} \times \textit{Higher-level branch indicator}_{i,t}\\&+ \textit{Fixed effects} + \textit{Distance and other Hard-information controls and interactions}_{i,t} + \varepsilon_{i,t},\\&\qquad\qquad t = \textit{2004-2006 (post-reform subsample only)}\end{aligned} \tag{3a}$$

$$\begin{aligned}&\textit{Loan term (or outcome)}_{i,t} = \beta^1 \textit{Predicted Rating}_{i,t} + \beta^2 \textit{Residual Rating}_{i,t} + \beta^3 \textit{Predicted}\\&\textit{Rating}_{i,t} \times \textit{Higher-level branch indicator}_{i,t} + \beta^4 \textit{Residual Rating}_{i,t} \times \textit{Higher-level branch}\\&\textit{indicator}_{i,t} + \textit{Fixed effects} + \textit{Distance and other Hard-information controls and}\\&\textit{interactions}_{i,t} + \varepsilon_{i,t},\\&\qquad\qquad t = \textit{2004-2006 (post-reform subsample only)}\end{aligned} \tag{3b}$$

where *i* indexes borrowers and *t* indexes years. The structure is not a true panel because many of the borrowers appear in the sample just once (1,259 firms have only one loan), but we do include year, city and industry fixed effects in all of the models, and we cluster standard errors by the borrower firms. The year effects absorb the direct impact of the *Post-2003* indicator (as well as absorbing macro conditions), so we only report its interaction with the soft-information index in the tables.

In estimating Equations (1)-(3), we report two models for loan price and one measure (one model) for loan size. The pricing measure is based on a normalized raw interest rate. As noted in Section II, the PBOC sets an upper and lower bound for interest rates that adjusts around a base rate. The base rate is set by the PBOC based on goals for macro-stabilization policy, so this base varies over time, as well as across loans with different maturities. As shown in Figure 1, the upper bound (as percentage of the base rate) rises over time while the lower bound remains the same (90% of the base rate). Therefore, using raw interest rates may generate biased coefficients because lenders can set much higher rates during later years of the sample (Table 1, Panel B). We therefore normalize interest rate to lie between zero and one using the following formula: normalized rate = (raw rate/base rate – 0.9)/(upper bound – lower bound). Hence, 0 represents the lowest possible rate that can be set in a given year (90% of the base rate), 1 represents the highest rate (set at the upper bound) in a given year, and for all the other raw interest rates their normalized value depends on deviation from the base rate as well as the gap between upper and lower bounds.

As shown in Table 1, the average normalized rate (0.79) during the pre-reform period is much higher than that (0.31) during the post-reform period, even though the average raw interest rate is higher in the post-reform period. These results are not surprising mainly because the upper bound rose significantly after the reform (from 130% of the base rates to 170% and then 250%) and a greater fraction of loans hit the upper bound during the pre-reform period. We report results from both the OLS models and (two-sided at both the upper and lower bounds) Tobit models to control for censored data issues (i.e., interest rates at the bounds). Finally, our non-price loan term equals the log of the amount of credit approved for the borrower on the loan, which we modeling using OLS.[8]

We study two measures for loan outcomes. First, we build an indicator equal to one for loans that are paid off in full and on time, and zero otherwise. We report logit regressions comparable to (1)-(3) above for this variable. Second, we exploit all of the variations in loan outcomes (*one year after* the loan maturity date is the cutoff for measuring late payments) with a variable that takes the value of zero for complete defaults, one for cases of partial repayment, two for cases of full payment but not on time, and three for cases of full and timely repayment. For this variable, we estimate an ordered logit model.

The key variables of interest in Equations (1)-(3) are the interaction effects between the soft information (internal credit ratings, and predicted and residual ratings) and: 1) the policy innovation (*Post-2003*); 2) an indicator equal to one if the loan officer (the person responsible for collecting information and building the soft-information) and manager (the holder of loan-approval decision rights) work in *different* branch offices.[9] We would expect that an increase in the credit rating, predicted rating or residual rating would lead to lower interest rates, greater credit limits, and better outcomes. The marginal effect of soft information (rating and residual rating) ought to strengthen after 2003 and when the loan is approved locally. Hence, we expect the same sign for β^1 and β^2 in Eq. (1), β^2 and β^4 in Eq. (2), and opposite signs for β^1 and β^3 in Eq. (3a) and for β^2 and β^4 in Eq. (3b). Whether the incremental effect of predicted rating is greater post-reform depends on the relative extent hard information is incorporated in ratings during the two periods.

[8] We would in principle also like to study the probability of loan approval, but this variable is not available in our dataset.

[9] Once again, we drop the data from the second half of 2002 and 2003, the period of the policy change.

Our measures of hard information include log of borrower assets, the return on assets (profits divided by assets in the year prior to loan origination), leverage (total debt before the loan / total assets), indicators for SOEs (state-owned) and privately owned firms (all the other ownership types, including mixture of local government and private ownerships, are the omitted group), and for loan types and purposes (e.g., fixed assets investment, real estate investment, and working capital). Each of the firm characteristics is measured in the year prior to loan origination. In some specifications, we include the full set of interactions between each of our hard information variables with the policy innovation (*Post-2003*). In the constrained specifications, we can assess how the relative weights on hard (predicted rating) v. soft (residual rating) information shift following reform and as a loan moves up the organizational hierarchy.

Table 1 reports summary statistics for firm characteristics (Panel A), loan terms (Panel B), and information on the bank branching hierarchy (Panel C). During the pre-reform sample the average firm asset size was RMB 338 million (about US$ 40.8 million), rising to RMB 745 million in the post reform sample; during the same period average loan size rises from RMB 5.3 million to RMB 7.7 million.[10] Leverage was slightly lower in the post-reform years (0.54 v. 0.48), whereas firm profitability was higher post reform (ROA rising from 7% to 9% at the mean). Despite better average characteristics based on hard information in the post-reform period, the internal soft-information credit score fell from 5.6 to 4.9 at the mean. Based our analysis shown above (Figure 2), we conclude that this is (partially) a result of increased rating conservatism post-reform. As shown in Panel C (information available on a subsample of loans during the post-reform period only), more than half of the loans are approved locally; as firm size increases (sorted by the size quintiles) the likelihood of local approval increases**.**

[10] We use RMB, the Chinese currency, to denote loan and firm size variables. The official exchange rate was US$1 = RMB 8.28 before 2005; despite (gradual) appreciation of the RMB over U.S. dollar and other major currencies since 2005, much debate remains on the extent to which the RMB is undervalued.

III.3 Results

Tables 3 and 4 report the main results for ex ante loan terms, that is, our estimate of Eq. (1) and (2); predicted and residual ratings are created by regressing the actual ratings on hard information variables (as in Table 2). We then examine the impact of hierarchy on soft information. We first study the factors associated with the decision to shift loan approval from the local branch where the credit rating is created to an upper-level branch (Table 5). Table 6 then reports expanded models that include the interaction between hierarchy indicators and soft information variables (Equations (3a) and (3b)). Table 7 reports descriptive statistics on loan outcomes, and Tables 8 and 9 report similar regression models using the loan outcome as the dependent variable.

Ex Ante Contract Terms

As discussed earlier, to obtain predicted and residual ratings, we run OLS regressions of actual ratings (1 to 8, higher is better) on hard information variables for the pre- and post-reform periods. From Table 2, the signs of these variables come in as expected in both periods: the ratings are higher for larger firms and firms with lower leverage and higher ROA. State-owned enterprises (SOEs) tend to receive lower ratings in both periods (relative to "other ownership types," the omitted group), reflecting loan officers' suspicion of their credit quality. Whereas privately owned firms also tend to receive lower ratings before the reform, they tend to get higher ratings after the reform.

The dependent variables in Table 3 are the normalized interest rate and the log of loan size. We report both OLS and two-sided (at the upper and lower bounds) Tobit models for the pricing term and OLS for the non-price term. For each dependent variable, we report an unconstrained specification in which we use the actual ratings while controlling for hard information variables (Eq. (1)). For this specification, we also interact each of the hard information variables for the borrowers with the post-2003 indicator to account for the fact that the lender might lower the weight placed on hard information as it increases the weight placed on soft information. We also report a constrained specification in which we use predicted ratings (and thus no hard information controls) and residual ratings obtained from Table 2 (Eq. (2)). In both specifications, we interact the post-2003 indicator with rating variables (with actual ratings in Columns 2, 4 and 6, and with both predicted and residual ratings in Columns 1, 3 and 5), and we include the industry, year and city fixed effects. We do not report the coefficients on the hard information variables and interactions between the hard information variables and the internal credit rating to save space.

The results in Table 3 suggest that increasing the accountability of loan officers improves the value of the soft information that they collect, thus allowing the lender to place more weight on soft information in setting loan terms. The effect of the soft information, proxied by the actual ratings (Columns 2, 4 and 6) or the residual ratings (Columns 1, 3 and 5), prior to the policy innovation, in fact, is small and not even statistically significant in either the pricing or credit limit equations. However, its effect becomes large, both statistically and economically, after the policy change. This is the case whether we use the actual ratings (while controlling for hard information variables) or the residual ratings. For example, based on the unconstrained model (Table 3, Column 2), increasing the credit rating (soft information) from the 25^{th} to the 75^{th} percentile (an increase of about 4 notches) lowers the normalized interest rate by 0.048, which is large relative to the standard deviation of the rate in the post-reform period of 21.8%. Raising the rating by 4 notches lowers loan size by about 10% post reform.

The predicted ratings, which we think of as a single-dimensional proxy for hard information incorporated into the credit rating, enters with the expected sign on loan terms for the whole sample—higher predicted ratings (lower borrower risk) leads to a reduction in interest rates and an increase in loan size. Interestingly, the impact of the predicted ratings on both interest rates and loan size falls sharply after the reform, consistent with the argument that lenders shift the weight in setting ex ante loan terms from hard information to soft information after reform. So, enhancing loan-officer accountability increases the usefulness of soft information; ex ante contract terms depend on soft information only after the responsibility for collecting the information resides clearly with loan officers (that is, only after 2003).

As discussed earlier, an advantage of the constrained approach is that the predicted rating absorbs the hard information about the borrower into a one-dimension variable, which allows us to directly compare the weights the bank places on hard versus soft information in setting loan terms in both the pre and post-reform periods. In order to do this, we first re-estimate the models in Table 3 separately for the pre- and post-reform periods, because the variations (esp. the dependent variables) are very different during the two periods. The results are presented in Table 4, Panel A. Consistent with the pooled sample results in Table 3, the impact of soft information on contract terms rises significantly after the reform: the coefficients on residual ratings (columns 1, 3, and 5) and actual ratings in the unconstrained models (columns 2, 4 and 6) are small (in magnitude) and not statistically significant; during the post-reform period the magnitude of the coefficients on residual ratings is ten times (columns 7, 9 and 11) that of those in the pre-reform period and are all statistically significant at 1%. On the other hand, while the predicted ratings do affect loan terms in both periods, the magnitude of the coefficients drops substantially after the reform.

We then obtain *standardized* regression coefficients (regression coefficients adjusted by the ratio of standard deviations of explanatory variables and dependent variables as shown in Panel B). Based on the standardized coefficients (Panel C), we can see that the impact of soft information (residual rating) on (normalized) interest rates goes from close to zero (and much smaller than that of predicated rating) pre-reform to a magnitude that is similar to that of the predicted rating in the post-reform period (a one-standard deviation increase in either the predicted or residual ratings results in a drop in interest rates by 8.5% to 10%), an increase of more than ten times. The impact of soft information on loan size also rises by a factor of ten, even though the magnitude is about one-fifth of that of the predicted rating in the post-reform period; notice, however, that this in part due to the fact the predicted rating absorbs the size effects (of the firms).

Since we have a much greater number of loans in the post-reform period than in the pre-reform period, which may reflects banks' expansion policies in lending (the economy was booming), one concern of the results reported in Tables 3 and 4 is that they may be driven by the possible changes in the distribution of loans. As a robustness check, we rerun tests in Tables 3 and 4 on a subsample of firms that borrow from the bank in *both* the pre- and post-reform periods (results not reported). The sample size drops (to about 8,000 loans) but we obtain similar results on the impact of ratings (actual, predicted and residual ratings) in the two periods. We conclude that the results obtained in Tables 3 and 4 are not due to a change in the distribution of loans over the two periods.

In Table 5 the dependent variable is a dummy equal to 0 if a loan is approved in the same branch where the credit rating is produced and 1 if the loan is approved at an upper-level branch. The (Logit) results provide support for our earlier discussions (in Section II.1), based on the bank's internal documents, that 'riskier' loans are more likely to be approved by an upper-level branch above which the credit rating is produced. Larger loans from smaller companies clearly represent greater default risk, and these loans are much more likely to be sent to upper-level branches for final approval. When we add other hard information control variables and the credit rating, the coefficients of loan and firm size do not change much and adding these additional controls only increases explanatory power slightly. As discussed earlier, we admit that we do not have exogenous variations on the hierarchy decision (during the post-reform period on a subset of loans), and we include all the hard information controls when we examine the impact of hierarchy on the use of soft information in Table 6.

Table 6 compares information usage across the internal hierarchy. The results from the unconstrained model (columns 2, 4 and 6 of Table 6) - using actual ratings and hard information variables - indicate that when a loan is approved at a higher-level branch, the impact of the ratings in setting interest rates and loan size declines. In fact, the sum of the coefficients on the rating plus the rating interacted with the higher-level branch indicator is not statistically significantly different from zero, meaning that there is *no relationship* between the rating and loan size for loans approved up the hierarchy. These results are consistent with theoretical predictions that hierarchy, or organizational distance, reduces individuals' incentive to produce soft information. I

In the constrained models, where we use only the predicted rating to capture hard information, we also find the higher branch indicator having an incrementally negative effect on residual ratings (columns 1, 3 and 5 of Table 6), but the coefficients on the interaction terms are not statistically significant. In fact, predicted ratings, again proxies for how hard information is used, have a *smaller* impact on interest rates for loans approved at higher-level branches (Columns 1 and 3). This appears to be inconsistent with theoretical predictions that in these cases hard information should be used *more* prominently (while soft information is discounted). However, we are cautious to draw this conclusion because we do not have exogenous variations across the hierarchy variable. The result probably reflects the fact that riskier loans are more likely to move up the hierarchy, and lending decisions may incorporate additional screening as a 'new set of eyes' determine the final terms of the loan.

Ex Post Outcomes

We have seen that the bank places greater weight on soft information when contracting problems between the loan officer and the management of the bank are better contained, both by placing greater responsibility on individual lenders and by having decisions taken at the branch level rather than at a higher level within the organization. This behavior supports the idea that the soft information itself is more informative when those internal agency problems are less severe.[11] We now test this idea directly by estimating whether the soft-information credit rating predicts outcomes better after reform than before, and when borrowers are closer to lenders. For our sample of loans, we are able to observe whether the borrower paid the lender on time or was in some kind of default state, using one year after the original loan maturity date as the cutoff date for late repayment. For example, of the 3,190 loans made in the pre-reform sample, 2,065 (about 2/3) paid off in full and on time. Of the other third, most borrowers paid off the loan (one year after the maturity date) but were late on some of the payments (1,096). During the post-reform period, where we have a larger sample of loans, the distribution was somewhat more favorable, with about 77% of loans performing on time. The better performance post-reform may be due in part to the policy change, although the economy overall performed better during these years than during the earlier period.

Table 7 reports the simple default statistics by credit rating, divided into pre- and post-reform regimes (Panel A), and, for the post-reform regime, based on whether the approval decision was taken within the same branch as the loan application or at a higher level (Panel B). Panel A shows, as noted earlier, that firms with credit scores below 3 appear to gain access to credit after reform, whereas they were rationed out of the market earlier. Comparing outcomes for firms rated 3 or better, the gradient appears steeper after the reform. For example, pre-reform the probability of full and timely repayment rises from 63.5% to 78% as the score moves from 3 to 8; post-reform this probability rises from 65% to 89%. Similarly, in the post-reform sample the credit score divides risks better when the decision rights reside within the branch where the application is first made (Panel B). For these loans, the repayment rate rises from 37% for the riskiest loans to100% for the

[11] We are not suggesting that having lending decisions taken out of the local branch is a mistake by the bank. Separating the contracting responsibility from the decision-making responsibility will reduce soft information's value (a cost), but may also mitigate corruption problems (a benefit) that could more than offset the reduction in the utility of soft information.

safest; in contrast, for loans decided at higher levels within the bank hierarchy, the repayment rate is much flatter, rising from 75% for riskiest loans to 100% for those in the safest category. In fact, variation from the lowest score (1) to the mid-range scores (4), the default probability first falls (from 75% to 64%), then begins to rise. By contrast, the risk-default profile is monotonically increasing up to the very safe loans scored above 6 for the sample where decisions are taken at the branch level.

Tables 8 and 9 report outcome regression results (coefficients) using the same structure that we had applied to the ex ante contract terms (recall Equations (1)-(3)). These models are similar in spirit to the conditional means in Table 7, but they control for all of the hard information variables and interactions terms (or use both predicted and residual ratings). From Table 8, loans to better rated firms default less, but the link from ratings to default does not change significantly after 2003. We obtain similar results in Table 9, where we introduce the hierarchy indicator and interaction terms. The predictability of loan outcomes does drop when the loan is approved at upper-level branches, but these changes (i.e. the interaction effects) are not statistically significant.

We have found that links from *ex ante* loan terms to soft information strengthen after reform but links to *ex post* outcomes do not change. This result makes sense if better use of information changes lender's ex ante control of risk. For example, in Tables 3 and 4 we find that the soft information contained in the ratings plays a more significant role in setting prices and credit limits after reform. Better control over credit limits may reduce default risk; this is looking at credit rationing on the intensive market (that is, smaller loans for riskier firms). Given better risk control, however, we would also expect an expansion of credit supply at the extensive margin. Moreover, better pricing of risk (due to better soft information) also ought to mitigate credit rationing and lead to lower loan denial rates, which would tend to raise rather than lower default rates. (Data on rejected loans is not available to us.) We conclude that the enhanced role of soft information in the lending process, as a result of the reform, works mostly through better setting *ex ante* loan contract terms and control borrower risk, thus likely expanding credit supply to risky borrowers but not necessarily lowering default rates.

IV. Conclusions

In this paper we examine how banks with different organizational and incentive structures produce and process soft information in setting both price and non-price terms of loan contracts. We use data from China, where the banking sector has historically been dominated by large, inefficient state-owned banks with centralized decision making processes. Following China's entrance to the WTO in December 2001, however, many banks, and in particular, state-owned banks, implemented a series of reforms in 2002 with the focus on decentralization—shifting the responsibilities of making lending decisions to individual officers working in branches that directly process loan applications. We view these reforms as plausibly exogenous shocks from the perspective of lending officers charged with processing soft information and contracting that strengthens their incentive to produce accurate soft information.

We utilize detailed (proprietary) loan-level data from a large, nationwide state-owned bank that specify not only contract terms – interest rates and loan size – but also the physical and organizational distance between the borrower and the lender. We find that incentives to produce soft information affect, first, how banks use that information and, second, how well that information forecasts loan performance. Better information, in turn, expands the supply of credit and improves (lending) outcomes. The reform also led to more 'conservatism' in that loan officers become less willing to assign higher ratings for the fear of being held liable for bad loans. We also find evidence that organizational and physical distance makes it more difficult to produce soft information. In particular, when the loan approval decision is made at the branch above which the risk assessment is made, the weight of the internal risk measure on loan contracts shifts toward hard information. In these cases it also becomes a poorer predictor of loan performance.

Our results are of particular relevance for emerging economies that aim to develop their financial institutions. Reforming organizational structures and providing more incentives for loan officers can have significantly improve the efficiency of financial institutions. Hierarchy, or organizational distance, on the other hand, can reduce the incentive, as much as physical distance, to produce soft information. Given the 'populist' demand for tighter regulations on financial institutions following the 2007-2009 global financial crisis, our results also call for more caution in excessive regulations as they may destroy the incentive structure to produce high-quality soft information, which is central in financial contracting and most business transactions.

Appendix A:
How Are Internal Ratings (Soft information) Created? Two Case Studies

Case 1:

Company A, a state-owned company, has been in the copper industry for a long time. Facing increasingly fierce competition, the company's performance has been slipping since 2000: Sales and profits dropped and losses started to pile up, and so was its leverage level. For the past few years it had delayed repayments to several bank loans, losing its traditionally sound credit history and reputation. In 2005, Company A applies for a new loan (for restructuring efforts) and if loan officers were to base their (internal) ratings solely on publicly available information and the firm's recent track record, Company A would receive a very low rating and its application would be rejected.

The loan officers in charge of the rating, however, found out that Company B, through its holding company and/or one of its divisions, was in negotiations to help Company A's restructuring efforts (through the formation of a strategic alliance). After numerous investigations and discussions with various officials from Company A, the loan officers obtained detailed information on the proposed restructuring plan (with Company B's role) as well as its strategic growth plan post-restructuring. With this information (not public and not verifiable as neither Company A or B would publicly make any announcement), along with their own evaluation of Company A's new products and market share, the officers adjusted their initial rating, which helped Company A secure the new loan. Company A eventually repaid the new loan on time and regained its reputable credit record.

Case 2:

Company C, a large textile company in its region and partially owned by the local government, has been struggling due to weakening demand of its products. Its financial conditions also worsened and the company seeks a new loan from the bank to secure liquidity and working capital needs. The company's executives lobbied various government officials to help 'strengthen' its relationship with the bank, as these executives were aware that it is unlikely that they will be able to convince the loan officers of their current credit worthiness. Given the strategic importance of the company, several officials did put in personal efforts in trying to convince the senior officials of the bank branch that handled the loan application.

The bank branch sometimes does not have the final say in cases of approving loans from 'risky' or questionable borrowers, rather the larger branch in the state capital (higher ranked along the hierarchy chain) does. However, since most of the interactions (e.g., loan applications and post-loan monitoring) with borrower companies take place in smaller branches throughout the state, it is important to have the support of government officials in the smaller cities and counties where the direct lending activities occur. Moreover, many city and county governments have considerable budget surpluses and there is fierce competition among all financial institutions to win over (the depository services) the 'special' customers.

Perhaps due to the persistent persuasions and pressure from local government officials, the loan officers in charge of the internal risk assessment of the loan (at the local branch) assigned a favorable rating to Company C, and this rating also helped to pave the way for the approval of the loan from the superior branch. However, Company C's fortune did not turn around and defaulted on the loan.

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Table 1: Summary Statistics on Loans

The sample data is from June 15, 1999 to December 31, 2006, with April 17, 2002 as the starting point for the policy reform. Pre-reform period indicates 6/15/1999 to 4/16/2002, and Post-reform period indicates 1/1/2004 to 12/31/2006; we drop loans originated between 4/17/2002 and 12/31/2003. Internal credit ratings range from 1 to 8, with a higher score indicating a borrower with higher credit quality. Distance to the nearest potential lender is the actual distance between the borrower firm's headquarter to the nearest branch of any lending institution in the same area. In Panel B, the normalized interest rate, between 0 and 1, is calculated using the formula: normalized rate = (raw rate/base rate – 0.9)/(upper bound - lower bound).

Panel A: Firm Characteristics

Variable		Pre reform period	Post reform period
Number of loans		3,190	18,605
Number of firms		1,498	3,462
Firm Assets (Million RMB)	Max	27,100.082	119,916.746
	Min	1.176	1.471
	Mean	338.508	745.071
Leverage	Max	1	1
	Min	0	0
	Mean	0.54	0.48
ROA	Max	0.74	0.99
	Min	-0.79	-0.23
	Mean	0.07	0.09
Credit Rating (1 is riskiest, 8 safest)	Max	8	8
	Min	1	1
	Mean	5.62	4.89
Distance to the Nearest Potential Lender (Km)	Max	80.52	76.47
	Min	0	0
	Mean	2.93	2.16
Firm type	State-owned	690	2,066
	Private	683	6,484
	Others	1,817	10,055
Industry	Agriculture	230	602
	Manufacturing	1,303	10,670
	Construction	72	415
	Utility	85	679
	Retailing	521	3,786
	Others	979	2,453

Panel B: Loan Terms			
Variable		Pre reform period	Post reform period
Actual Interest Rate (%)	Max	7.84	14.63
	Min	4.54	4.54
	Mean	6.89	7.25
Normalized Int. Rate (0 to 1)	Max	1	1
	Min	0	0
	Mean	0.79	0.31
Loan Size (Million RMB)	Max	300	1,500
	Min	0.5	0.5
	Mean	5.308	7.724
Loan Purpose	Working capital	3,048	18,450
	Fixed asset	25	17
	Real estate	117	138

Panel C: Information on Hierarchy (available for the post-reform period only)			
Variable		Approved within the same branch	Approved in higher branch
Number of loans		2,237	2,022
Number of firms		881	811
Firm size	<=20%	378	474
	20%~40%	398	456
	40%~60%	432	417
	60~80%	442	408
	>80%	587	267

Table 2: Regression of Credit Ratings on Hard information Variables

We report OLS regression results of internal ratings on hard information variables. The SOE dummy equals 1 when the borrower is a state-owned enterprise, and 0 otherwise; Private firms dummy equals 1 when the borrower firm is privately owned, and 0 otherwise ("other ownership types" are the default type). Fixed assets dummy = 1 when the purpose of loan is for purchasing fixed assets, and 0 otherwise; Real estate assets dummy = 1 when the purpose of loan is for purchasing real estate assets, and 0 otherwise. Standard errors are clustered by borrower firms.

Independent Variable	Pre-reform (Pre-2003)	Post reform (Post-2003)
Log asset	**0.137**	**0.362**
	(0.000)	(0.000)
Leverage	**-0.743**	**-1.808**
	(0.000)	(0.000)
ROA	**1.313**	**6.747**
	(0.001)	(0.000)
SOE	**-0.383**	**-0.512**
	(0.000)	(0.000)
Private	**-0.153**	**0.161**
	(0.049)	(0.000)
Fixed asset	-0.032	0.031
	(0.924)	(0.939)
Real estate	**-0.406**	**-0.665**
	(0.010)	(0.000)
Total mean square	2.775	3.336
RMSE	1.639	1.643
R squared	0.0344	0.1908
F test	0.0000	0.0000
No. of Obs.	3,190	18,605

P-values appear below coefficients.

Table 3: Regression of Loan Terms on Hard and Soft Information: Pre v Post-Reform

We report regression (OLS and two-sided Tobit) results of loan terms (normalized interest rate and log of loan size) on soft and hard information. The Post-reform dummy equals 1 when the loan is made after the reform (post-2003). Predicted ratings and residual ratings are generated from Table 2 for both the pre- and post-reform periods. Firm controls and interactions include financial variables (firm size, leverage, ROA), loan purpose (fixed asset loan, real estate loan), ownership types (SOE, private) and the interactions between post-reform indicator and financial variables. Normalized rate (between 0 and 1) is calculated using the formula: Normalized rate = (raw rate/base rate – 0.9)/(upper bound - lower bound). Standard errors are clustered by borrower firms.

Independent variable	Normalized rate (OLS)		Normalized rate (Tobit)		Log loan size (OLS)	
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted rating	**-0.113**		**-0.159**		**1.213**	
	(0.000)		(0.000)		(0.000)	
Post*predicted	**0.087**		**0.130**		**-0.779**	
	(0.001)		(0.000)		(0.000)	
Residual rating	0.002		0.010		0.000	
	(0.753)		(0.151)		(0.986)	
Post*residual	**-0.013**		**-0.024**		**0.040**	
	(0.015)		(0.001)		(0.051)	
Actual rating		0.002		0.010		-0.002
		(0.737)		(0.107)		(0.870)
Post*actual		**-0.012**		**-0.023**		0.023
		(0.025)		(0.001)		(0.125)
Firm controls & interactions	No	Yes	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs	21,795	21,795	21,795	21,795	21,795	21,795
R square	0.7479	0.7689	NA	NA	0.2707	0.5613
F test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

P-values appear below coefficient

Table 4: Regression of Loan Terms on Hard and Soft Information: Pre v Post-Reform and Standardized Coefficients

In Panel A we report regression (OLS and two-sided Tobit) results of loan terms (standardized interest rate and log of loan size) on soft and hard information in the pre- and post-reform periods separately. Predicted ratings and residual ratings are generated from Table 2 for both the pre- and post-reform periods. Firm controls include financial variables (firm size, leverage, ROA), loan purpose (fixed asset loan, real estate loan), ownership types (SOE, private). Normalized (interest) rate (between 0 and 1) is calculated using the formula: Normalized rate = (raw rate/base rate – 0.9)/(upper bound - lower bound). In all models we include year dummies, industry dummies, and city dummies. Standard errors are clustered by borrower firms.

Panel A: Regression results for Pre- and Post-reform periods												
Independent variable	Pre reform (before 2003)						Post reform (after 2003)					
	Normalized rate (OLS)		Normalized rate (Tobit)		Log loan size (OLS)		Normalized rate (OLS)		Normalized rate (Tobit)		Log loan size (OLS)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Predicted rating	**-0.131**		**-0.180**		**1.217**		**-0.026**		**-0.029**		**0.432**	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Residual rating	0.001		0.001		-0.004		**-0.011**		**-0.012**		**0.042**	
	(0.917)		(0.897)		(0.812)		(0.000)		(0.000)		(0.000)	
Actual rating		0.001		0.002		-0.008		**-0.010**		**-0.011**		**0.020**
		(0.839)		(0.844)		0.560		(0.000)		(0.000)		(0.003)
Firm controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No of Obs	3,190	3,190	3,190	3,190	3,190	3,190	18,605	18,605	18,605	18,605	18,605	18,605
R square	0.3666	0.4693	NA	NA	0.3018	0.5470	0.6850	0.7069	NA	NA	0.2557	0.5579
F test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

P-values appear below coefficients.

In Panel B we report standard deviations of the dependent and main independent variables for both the pre- and post-reform periods (from Panel A). In Panel C we report standardized coefficients for Xi is obtained by the following formula: standardized coefficient of Xi = Coefficient of Xi*(standard deviation of Xi/standard deviation of Y).

Panel B: Standard Deviations of the regression variables

Variable	Pre reform (before 2003)	Post reform (after 2003)
Normalized rate	0.255	0.218
Log loan size	1.079	1.056
Predicted rating	0.309	0.798
Residual rating	1.637	1.642
Actual rating	1.666	1.826

Panel C: Standardized Coefficients

Independent variable	Pre reform						Post reform					
	Normalized rate (OLS)		Normalized rate (Tobit)		Log loan size (OLS)		Normalized rate (OLS)		Normalized rate (Tobit)		Log loan size (OLS)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Predicted rating	-0.158		-0.217		0.348		-0.097		-0.104		0.326	
Residual rating	0.003		0.008		-0.007		-0.085		-0.094		0.066	
Actual rating		0.007		0.011		-0.012		-0.083		-0.092		0.035

Table 5: Determinants of Approving Loans Locally vs. Moving up the Hierarchy

This table report Logit regression coefficients on the determinants of where a loan is approved. The dependent variable is a dummy that equals 0 if a loan is approved at the same branch that the internal credit rating is produced, and equals 1 if it is approved at a higher-level branch. Explanatory variables include hard information variables, log of loan size, and the credit rating on the loan. Standard errors are clustered by borrower firms.

Independent variable	Estimators	Estimators
	P value	P value
Log Loan size	**0.238**	**0.247**
	(0.001)	(0.001)
Log asset	**-0.376**	**-0.279**
	(0.000)	(0.000)
Leverage		-0.460
		(0.212)
ROA		0.961
		(0.227)
Soft info		**-0.237**
		(0.000)
SOE		**0.775**
		(0.000)
Private		**0.558**
		(0.000)
Industry Dummies	Yes	Yes
Year Dummies	Yes	Yes
City fixed effects	Yes	Yes
Pseudo R square	0.4863	0.4991
X2 test	0.0000	0.0000
Number of observations	4,245	4,245

P-values appear below coefficients.

Table 6: Regression of Ex Ante Loan Terms on Hard and Soft Information: Effect of Hierarchy

We report OLS regression results of loan terms (interest rate and log of loan size) on soft and hard information *Higher-level branch* dummy equals 0 when the loan is approved by the branch where internal rate was calculated, and it equals 1 when the loan is approved by an upper-level branch. Normalized rate (between 0 and 1) is calculated using the formula: normalized rate = (raw rate/base rate – 0.9)/(upper bound - lower bound). Standard errors are clustered by borrower firms.

Independent variable	Normalized rate (OLS)		Normalized rate (Tobit)		Log loan size (OLS)	
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted rating	**-0.023**		**-0.023**		**0.505**	
	(0.000)		(0.000)		(0.000)	
High-level branch indicator *Predicted	**0.010**		**0.010**		-0.039	
	(0.039)		(0.038)		(0.543)	
Residual rating	**-0.015**		**-0.015**		**0.065**	
	(0.000)		(0.000)		(0.012)	
High-level branch indicator *Residual	0.004		0.004		-0.006	
	(0.194)		(0.179)		(0.887)	
High-level branch indicator	-0.021	0.029	-0.021	0.027	0.181	-0.536
	(0.449)	(0.613)	(0.438)	(0.633)	(0.589)	(0.249)
Actual rating		**-0.013**		**-0.014**		**0.040**
		(0.000)		(0.000)		(0.018)
High-level branch indicator *Actual		**0.005**		**0.005**		**-0.047**
		(0.075)		(0.068)		(0.075)
Firm controls & interactions	No	Yes	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs	4,259	4,259	4,259	4,259	4,259	4,259
R square	0.7060	0.7324	NA	NA	0.2596	0.5474
F test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

P-values appear below coefficients.

Table 7: Summary Statistics on Loan Performance

This table reports the simple default statistics sorted by internal credit ratings, divided into pre- and post-reform regimes (Panel A), and, for the post-reform regime, based on whether the approval decision was taken within the same branch as the loan application or at a higher level (Panel B). "Pay off on time" means the borrower pays off the entire loan on or before the maturity date, otherwise the borrower is in some kind of default state (3 cases), using one year after the original loan maturity date as the cutoff date for (late) repayment.

Panel A: Performance for the whole sample

Time period		Pre reform period (pre-2003)								Post reform period (Post-2003)							
Soft-info credit rating		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Breach of contract	Didn't repay	0.0%	0.0%	2.0%	0.0%	0.0%	0.5%	0.2%	2.9%	0.5%	0.5%	1.0%	1.3%	0.6%	1.2%	1.9%	0.0%
	Partially repay	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.2%	0.4%	0.4%	0.5%	0.2%	0.2%	0.1%	0.0%
	Pay off late	83.3%	0.0%	34.5%	40.6%	46.7%	42.6%	26.2%	19.0%	42.6%	45.8%	33.6%	27.6%	19.9%	9.4%	10.2%	10.7%
Performance of contracts	Pay off on time	16.7%	0.0%	63.5%	59.4%	53.3%	56.6%	73.6%	78.2%	56.8%	53.2%	65.1%	70.7%	79.3%	89.2%	87.7%	89.3%
Total (100%)		6	0	510	495	240	744	810	385	1,510	954	1,886	1,244	5,374	3,474	4,041	122

Panel B: Performance for the post reform sub-sample

Higher branch indicator		0 (approved within the same branch)								1 (approved in a higher branch)							
Soft-info credit rating		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Breach of contract	Didn't repay	0.0%	0.0%	1.8%	0.8%	0.0%	0.4%	0.2%	0.0%	0.0%	0.0%	1.4%	0.0%	0.0%	0.2%	0.6%	0.0%
	Partially repay	1.0%	1.1%	3.5%	1.6%	0.2%	0.2%	0.2%	0.0%	0.0%	0.0%	0.7%	0.0%	0.9%	0.3%	0.0%	0.0%
	Pay off late	62.4%	46.0%	27.6%	18.5%	9.0%	4.4%	6.4%	0.0%	25.0%	32.3%	34.0%	21.8%	19.5%	8.2%	2.9%	0.0%
Performance of contracts	Pay off on time	36.6%	52.9%	67.1%	79.1%	90.8%	95.0%	93.2%	100.0%	75.0%	67.7%	63.9%	78.2%	79.7%	91.3%	96.5%	100.0%
Total (100%)		101	87	170	249	556	544	512	18	28	62	147	147	467	634	518	19

Table 8: Regression of Loan Outcomes on Hard and Soft Information: Pre v. Post-Reform

We report Logit and Ordered Logit regression results (coefficients) of loan performance outcomes on soft and hard information. In the Logit models (columns 1-2), the dependent variable equals 1 if a loan is paid in full at the maturity date, and 0 otherwise; in the Ordered Logit models (columns 3-4), the dependent variable equals 0 when a loan makes no payment *one year after* the loan maturity date, equals 1 when it makes partial payment one year after maturity, equals 2 when it makes full payment one year after maturity and 3 when it makes *full payment on the loan maturity date*. Standard errors are clustered by borrower firms.

Independent variable	Logit for default		Ordered logit	
	(1)	(2)	(3)	(4)
Predicted rating	**0.462**		**0.471**	
	(0.023)		(0.016)	
Post*predicted	0.239		0.205	
	(0.248)		(0.305)	
Residual rating	**0.176**		**0.169**	
	(0.000)		(0.000)	
Post*residual	0.020		0.021	
	(0.646)		(0.624)	
Actual rating		**0.177**		**0.170**
		(0.000)		(0.000)
Post*actual		0.017		0.018
		(0.709)		(0.683)
Firm controls & interactions	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes
No of obs	21,795	21,795	21,795	21,795
X2 test	0.0000	0.0000	0.0000	0.0000

P-values appear below coefficients.

Table 9: Regression of Loan Outcomes on Hard and Soft Information: Effect of Hierarchy

We report Logit and Ordered Logit regression results (coefficients) of loan performance outcomes on soft and hard information. *Higher-level branch* dummy equals 0 when the loan is approved by the branch where internal rate was calculated, and it equals 1 when the loan is approved by an upper-level branch. In the Logit models (columns 1-2), the dependent variable equals 1 if a loan is paid in full at the maturity date, and 0 otherwise; in the Ordered Logit models (columns 3-4), the dependent variable equals 0 when a loan makes no payment *one year after* the loan maturity date, equals 1 when it makes partial payment, equals 2 when it makes full payment one year after the loan maturity date, and 3 when it makes *full payment on the loan maturity date*. Standard errors are clustered by borrower firms.

Independent variable	Logit for default		Ordered logit	
	(1)	(2)	(3)	(4)
Predicted rating	**1.34**		**1.217**	
	(0.000)		(0.000)	
High-level branch indicator *predicted	0.022		0.090	
	(0.915)		(0.630)	
Residual rating	**0.629**		**0.584**	
	(0.000)		(0.000)	
High-level branch indicator *residual	-0.159		-0.138	
	(0.126)		(0.152)	
High-level branch indicator	-0.020	-2.19	-0.376	-2.315
	(0.985)	(0.313)	(0.699)	(0.256)
Actual rating		**0.631**		**0.589**
		(0.000)		(0.000)
High-level branch indicator *actual		-0.173		-0.156
		(0.101)		(0.112)
Firm controls & interactions	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes
No of obs	4,126	4,126	4,126	4,126
X2 test	0.0000	0.0000	0.0000	0.0000

P-values appear below coefficients.

Figure 1 (Regulated) Interest Rate Movements

Below is the timeline of changes in regulations on loan interest rates (base rates and upper and lower bounds) from June 10, 1999 to December 31, 2005 in China. Floating band indicates the range in which interest rates can fluctuate (e.g., set by lenders) from the base rate: for example, a floating band [90%, 130%] means that the lowest possible rate is 90% of the base rate while the highest rate is 130% of the base rate. Base rates are time varying (regulation changes) and depend on loan maturities.
Source: People's Bank of China, *Almanac of China's Finance and Banking* (2000-2008)

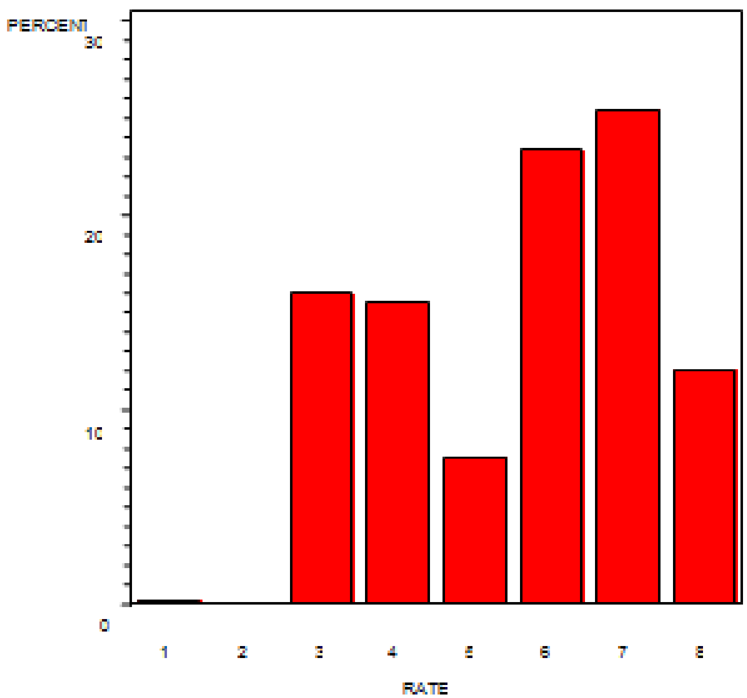
June 10, 1999, Floating band: [90%, 130%]

February 21, 2002: Base interest rate drops; floating band: [90%, 130%]

January 1, 2004: Base interest rate remains constant (from previous period); floating band: [90%, 170%]

October 29, 2004: Base interest rate rises; floating band: [90%, 230%]

Histogram of *actual* ratings during pre-2003 (pre-reform) period



Histogram of *actual* ratings during post-2003 (after reform) period

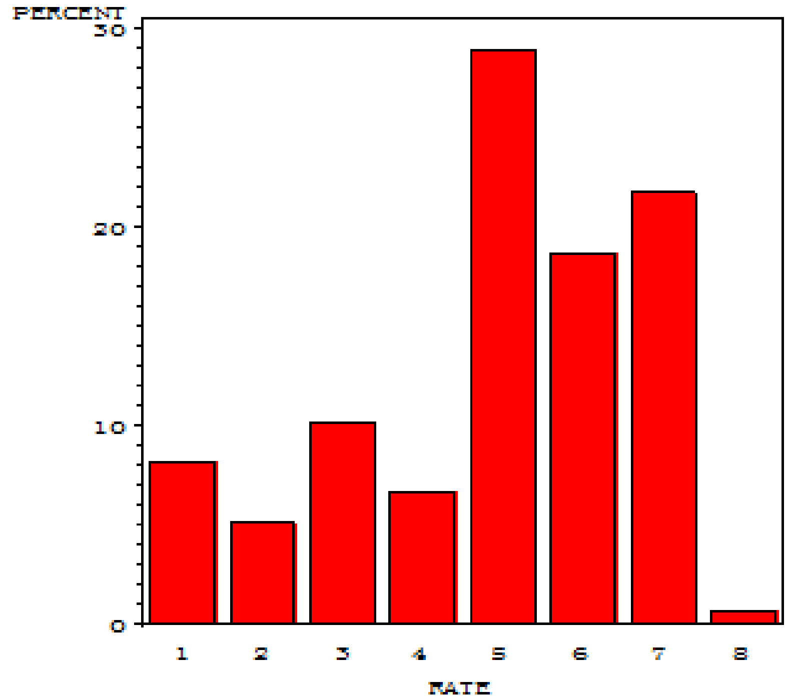
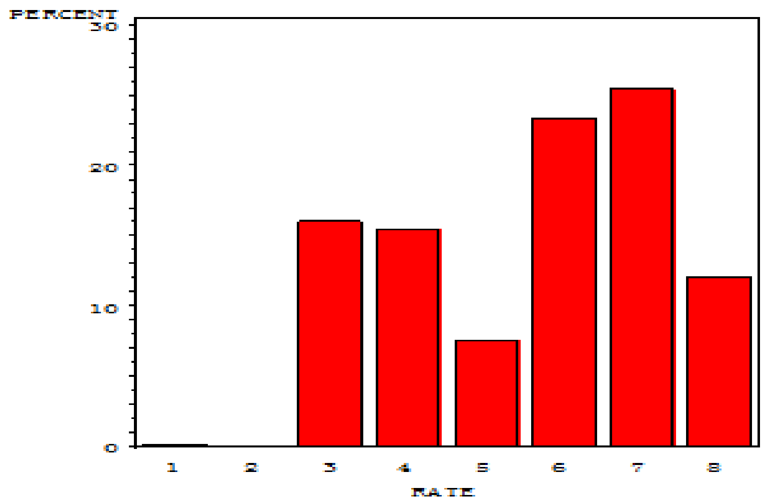


Figure 2, Panel A: Distributions of Actual Internal Ratings

In Panel A of Figure 2 we plot the histograms of actual internal ratings on loans during the pre-2003 (before reform, top figure) and post-2003 (after reform, bottom figure) periods. There are 3,190 loans in the pre-2003 sample and 18,605 loans in the post-2003 sample. Internal ratings range from 1 to 8; higher ratings indicating higher credit quality.

Histogram of *actual* ratings during the pre-reform (pre-2003) period



Histogram of *predicted* ratings during pre-reform period

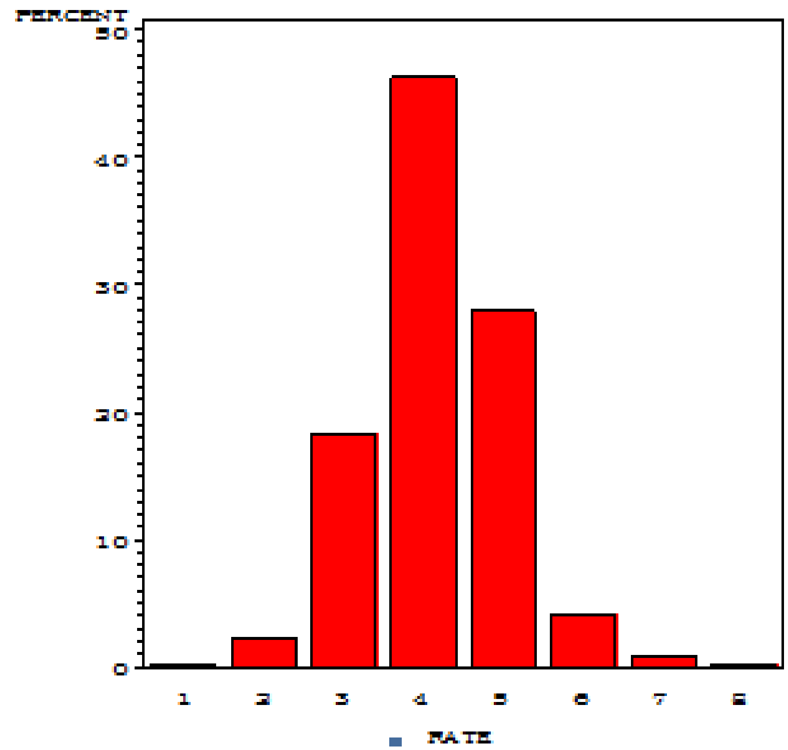


Figure 2, Panel B: Comparing the Dist. of Actual vs. Predicted Ratings in the Pre-2003 Period

In Panel B of Figure 2 we plot the histograms of actual internal ratings during the pre-2003 period (top figure) and the distribution of *predicted* ratings during the same period (bottom figure). Internal ratings range from 1 to 8; higher ratings indicating higher credit quality.

In order to obtain predicted ratings, we first run the following regression on the post-reform period:

Rating = b0 + b1*log(asset) + b2*leverage + b3*ROA + b4*SOE + b5*private + b6*log(1+min.dist.) + Industry dummies + City dummies + error term.

We then use the pre-reform (hard) information on a loan and regression coefficients to obtain the predicted rating for the loan (all the predicted values are adjusted to the nearest integer).