Bank Credit Cycles[*]

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Abstract

Private information about prospective borrowers produced by a bank can affect rival lenders due to a "winner's curse" effect. Strategic interaction between banks with respect to the intensity of costly information production results in endogenous credit cycles, periodic "credit crunches." Empirical tests of this repeated lending game are constructed based on parameterizing public information about relative bank performance that is at the root of banks' beliefs about rival banks' behavior. Consistent with the theory, we find that the relative performance of rival banks has predictive power for subsequent lending in the credit card market, where we can identify the main competitors. At the macroeconomic level, we show that the relative bank performance of commercial and industrial loans is an autonomous source of macroeconomic fluctuations. In an asset pricing context, we find that the relative bank performance is a priced risk factor for both banks and nonfinancial firms. The factor-coefficients for non-financial firms are decreasing with size, consistent with smaller firms being more bank-dependent.

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1. Introduction

are sticky, banks do, in fact, change their lending standards.[4] The most direct evidence comes from the Federal Reserve System's Senior Loan Officer Opinion Survey on Bank Lending Practices.[5] Banks are asked whether their "credit standards" for approving loans (excluding merger and acquisition-related loans) have "tightened considerably, tightened somewhat, remained basically unchanged, eased somewhat, or eased considerably." Lown and Morgan (2005) examine this survey evidence and note that, except for 1982, every recession was preceded by a sharp spike in the percentage of banks reporting a tightening of lending standards. Other evidence that bank lending standards change is econometric. Asea and Blomberg (1998) examined a large panel data set of bank loan terms over the period 1977 to 1993 and "demonstrate that banks change their lending standards - from tightness to laxity - systematically over the cycle" (p. 89). They concluded that cycles in bank lending standards are important in explaining aggregate economic activity.

Also in a macroeconomic context, changes in the Fed Lending Standards Index (the net percentage of respondents reporting tightening) Granger-causes changes in output, loans, and the federal funds rate, but the macroeconomic variables are not successful in explaining variation in the Lending Standards Index.[6] The Lending Standards Index is exogenous with respect to the other variables in the Vector Autoregression system. See Lown and Morgan (2005, 2002) own w 10.98 0 0 10.98

production about prospective borrowers.[9] A bank can strategically produce more information than its rivals and then select the better borrowers, leaving unknowing rivals with adversely selected loan portfolios. Unlike standard models of imperfect competition, following Green and Porter (1984), there are no price wars among banks since banks do not change their loan rates. However, as in Green and Porter (1984), intertemporal incentives to maintain the collusive arrangement requires periods of "punishment." Here these correspond to credit crunches. In a credit crunch all banks increase their costly information production intensity, that is, they raise their "lending standards," and stop making loans to some borrowers who previously received loans. These swings in credit availability are caused by banks' changing beliefs, based on public information about rivals, about the viability of the collusive arrangement.

Empirically testing models of repeated strategic interaction of firms has focused on price wars. See Reiss and Wolak (2003) and Bresnahan (1989) for surveys of the literature. However, our model predicts that there are "information production wars." Since information production is unobservable, we can not follow the usual empirical strategy. We propose a new method for testing the model. In particular, we empirically proxy for agents' beliefs using parameterizations of the information that is available for belief formation. In the context of banking, information about rivals is controlled by bank regulators which collect and release these data at regular intervals. Using measures that concern rival banks' relative performance, encapsulated in a Performance Difference Index (*PDI*) which we construct, we can test a general implication of any equilibrium of the model with imperfect competition by identifying the relevant public information and its relation with "information production wars"--credit crunches.

In particular, we show theoretically that to detect deviations by rival banks, each bank looks at two pieces of public information: the number of loans made in the period by each rival and the default performance of each rivals' loan portfolio. This is an implication of banks competing using information production intensity (lending standards). We argue that the relative performance of other banks is the public information relevant for each bank's decisions about the choice of the level of information production. Intuitively, excessive information production by a bank will not change the overall loan performance on average, but will change the distribution of loan defaults across banks. Moreover, the use of relative bank performance empirically distinguishes our theory from a general learning story, which would predict past bank performance matters for bank credit decisions (an alternative hypothesis which we test).

Broadly, the empirical analysis is in three parts. First, we examine a narrow category of loans, U.S. credit card lending, where there are a small number of banks that appear to dominate the market. Even with a small number of banks it is not obvious which banks are rivals, so we first analyze this lending market by examining banks pairwise. If the *PDI* increases, banks should reduce their lending and increase their information production resulting in fewer loan losses in the next quarter. We also examine big credit card lender banks' profitability, using stock returns.

Second, we turn to the macro economy by looking at all commercial and industrial loans. We analyze a number of macroeconomic time series, including the Lending Standard Survey Index. We form an aggregate bank Performance Difference Index based on the absolute value of the differences on all commercial and industrial loans of the largest 100 banks. If beliefs are, in fact,

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[9] Strategic interaction between banks seems natural because banking is highly concentrated. Entry into banking is restricted by governments. In developed economies the share of the largest five banks in total bank deposits ranges from a high of 81.7% in Holland to a low of 26.3% in the United States. See the Group of Ten (2001). In less developed economies, bank concentration is typically much higher (see Beck, Demirguc-Kunt, and Levine (2003)).

based on this information, then we should be able to explain (in the sense of Granger causality) the time series behavior of the Lending Standard Survey responses (the percentage of banks reporting "tightening" their standards)

Finally, if credit crunches are endogenous, and a systematic risk, then they should be a priced factor in an asset pricing model of stock returns. Therefore, our final test is to ask whether the parameterization of banks' relevant histories is a priced risk factor in a four factor Fama-French asset pricing setting. We look at banks and nonfinancial firms by size, as credit crunches have larger effects on smaller firms. We find all the evidence to be consistent with the theory.

Two related theoretical models are provided by Dell'Ariccia and Marquez (2004) and Ruckes (2003). These papers show a link between lending standards and information asymmetry among banks, driven by exogenous changes in the macroeconomy. As distinct from these models, the fluctuation of banks' lending behavior in our paper is purely driven by the strategic interactions between banks instead of an exogenously changing economic environment.

In terms of empirical work, Rajan (1994) is related. He argues that fluctuations in credit availability by banks are driven by bank managers' concerns for their reputations (due to bank managers having short horizons), and that consequently bank managers are influenced by the credit policies of other banks. Managers' reputations suffer if they fail to expand credit while other banks are doing so, implying that expansions lead to significant increases in losses on loans subsequently.[10] We test Rajan's idea in the empirical section.

Also related to our work, though more distantly, is some research in Monetary Theory, in particular on the "bank lending channel."[11] The "bank lending channel" posits that disruptions in the supply of bank loans can be caused by monetary policy, resulting in credit crunches (see Bernanke and Blinder (1988)). If bank funding is interest rate sensitive, then perhaps changes in banks' cost of funds results in variation in the amount of credit that banks supply. The bank lending channel is controversial because, as some have argued, banks have access to non-deposit sources of funds. See Ashcraft (2003) for evidence against the bank lending channel. We do not investigate the effects of monetary policy here, though this is a topic for future research. We provide the micro foundations for how bank competition can cause credit crunches independent of monetary policy, but this is not mutually exclusive from the bank lending channel. However, like the bank lending channel, we assume that there are no perfect substitutes for bank loans, so that if borrowers are cut off from bank credit they cannot find alternative financing at the same price, especially small firms. Large firms usually have access to capital markets.

We proceed in Section 2 to first describe the stage game for bank lending competition, and we study the existence of stage Nash equilibrium and the model's implications for lending standards, and the stage game is followed by repeated competition. In Section 3, we carry out empirical tests. Section 4 concludes the paper.

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[10] However, as pointed out by Weinberg (1995), the data on the growth rate of total loans and loan charge-offs in the United States from 1950 to 1992 do not show the pattern of increases in the amount of lending being followed by increases in loan losses.

[11] The credit channel of monetary policy transmission has focused on the two ways that central bank action can affect real economic activity by increasing the "external finance premium" (see Bernanke and Gertler (1995) for a review). One of these is the "balance sheet channel," which is concerned with effects of monetary policy on firms' credit worthiness. Increases in interest rates, for example, may reduce the value of the collateral that firms borrow against. The other is the "bank lending channel," which is more relevant for our work.

2. The Lending Market Game

We first set forth the lending market stage game. To simplify our discussion, suppose that there are two banks in the market competing to lend, as follows. There are N potential borrowers in the credit market. Each of the potential borrowers is one of two types, good or bad. Good types' projects succeed with probability p_g, and bad types' projects succeed with probability p_b, where $p_g > p_b \geq 0$. Potential borrowers, sometimes also referred to below as "applicants," do not know their own type. At the beginning of the period potential borrowers apply simultaneously to each bank for a loan. There is no application fee. The probability of an applicant being a bad type is λ, which is common knowledge.[12] Each applicant can accept at most one loan offer, and if a loan is granted, the borrower invests in a one period project which will yield a return of $X < \infty$ if the project succeeds and returns 0 otherwise. A borrower whose project succeeds will use the return X to repay the loan, i.e., a borrower's realized cash flow is verifiable.

Banks are risk-neutral. They can raise funds at some interest rate, assumed to be zero. After receiving the loan applications, a bank can use a costly technology to produce information about the applicant's type. The credit worthiness testing results in determining the type of an applicant, but there is a per applicant cost of $c > 0$. Banks can test any proportion of their applicants. Let n_i denote the number of applicants that are tested by bank i. We say that the more applicants that a bank tests, i.e., using the costly information production technology, the higher are its credit or lending standards.[13] If a bank switches from not using the credit worthiness test to using it, or tests more applicants, we say that the bank has raised its lending or credit standards. We assume that neither bank observes the other bank's credit standards, i.e., each bank is unaware of how many applicants the other bank tests. Results of the tests are the private information of the testing bank.

Since the bank borrowing rate is zero, when a bank charges F (to be repaid at the end of the period) for one unit of loan, the bank's expected return from lending to an applicant will be $\lambda p_b F + (1-\lambda)p_g F - 1$ in the case of no credit worthiness testing. We assume:

- Assumption 1: $p_g X > 1$, $p_b X < 1$, and $\lambda p_b X + (1-\lambda)p_g X > 1$.

Assumption 1 means that there exists some interest rate, X, that allows a bank to earn positive profits from lending to a good type project ex ante, but there does not exist an interest rate at which a bank can make positive profits from lending to a bad type project ex ante. (Given the loan size being normalized to 1, the face value of the loan F uniquely determines the interest rate, and later on we refer to F as the "loan interest rate.") It is also possible for banks to profit from lending to both types of applicants without discriminating between the types.

Each bank first chooses some (could be zero, could be all) applicants to test, then, depending on the test results, decides whether to make a loan offer for each applicant, and if yes, at what interest rate. We formally define the stage strategy of each bank in the Appendix A. We assume

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[12] We will hold λ fixed throughout the analysis, but this is to clarify the mechanism that is our focus. It is natural to think of λ as being time-varying, representing other business cycle shocks outside the model, and we could easily incorporate this. But it would obscure the cyclical effects that are purely due to bank competition.

[13] Imagine that banks always produce some minimal amount of information about loan applicants. We ignore this base amount of information, however, and focus only on the situation where banks choose to produce more information than this base level. So, we interpret the credit worthiness test as the additional information produced, beyond the normal information production.

that banks do not observe each other's interest rates or the identities of applicants offered loans. At the end of the period only final loan portfolio sizes and outcomes are publicly observable. Banks cannot communicate with each other.
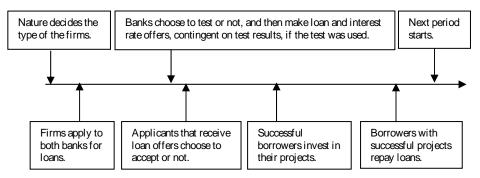

Figure 1: The Timing of the Stage Game

2.1 Stage Nash Equilibrium

We now turn to study Nash equilibrium, and the conditions for the existence of Nash equilibrium, in the lending market stage game. We show that in the stage game, banks have no incentive to conduct the credit worthiness tests, and we provide a condition under which the only Nash equilibrium that exists is one in which neither bank conducts credit worthiness testing and both banks earn zero profits.

First we will study the Nash equilibrium in which no bank conducts credit worthiness testing. We have the following results:

Proposition 1 *If and only if* $c \geq \dfrac{\lambda(1-\lambda)(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$, *does there exists a symmetric Nash equilibrium in which no bank conducts credit worthiness testing and both banks earn zero profits.*

The proof is in Appendix B.

Proposition 1 says that if the cost of testing each loan applicant is sufficiently high, i.e., $c \geq \dfrac{\lambda(1-\lambda)(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$, then the there exists a Nash equilibrium in which no bank conducts credit worthiness testing and neither bank earns positive profits.

- Assumption 2: $c \geq \dfrac{\lambda(1-\lambda)(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$.

Assumption 2 guarantees the existence of the stage symmetric Nash equilibrium. At the same time, this assumption implies that the optimal payoffs for the banks are reached when no credit worthiness testing are conducted (as we will show in a moment).

Now consider the case where both banks test at least some applicants.

Proposition 2 *There is no symmetric Nash equilibrium in which both banks test at least some of the applicants.*

The proof is in Appendix C.[14]

Intuitively, after the banks test some of the applicants, they will compete with each other for the good type applicants, which will drive the post-test profit to zero. However, since there is a test cost, ex-ante the banks' profits will be negative.

Our conclusion with regard to the stage game in the lending market is that, without mixed strategies, the only Nash equilibrium that exists is the equilibrium in which neither bank conducts credit worthiness testing, and both banks earn zero profits.

It is straightforward to characterize the optimal payoffs that the two banks receive in the stage game. If a bank does not conduct credit worthiness testing on an individual applicant and charges F, then the expected payoff from a loan to that individual applicant is $\pi = \lambda p_b F + (1 - \lambda) p_g F - 1$, which is maximized at $F = X$. If a bank conducts credit worthiness testing on an individual applicant and charges F, then the expected payoff from a loan to that individual applicant is $\pi' = (1 - \lambda) p_g F - 1 - c$, which also is maximized at $F = X$. It is easy to check that $\pi' < \pi$ with $F = X$ under Assumption 2.

2.2 Repeated Competition

We formalize the repeated game in Appendix D. In the stage game, we have already shown that banks earn zero profits without testing, and the optimal payoffs for banks are reached when there is no costly credit worthiness test being used. Setting a (collusive) loan interest rate of $F = X$ would be the most profitable case for both banks. Ideally, in repeated competition banks will try to collude to charge $F = X$ without conducting credit worthiness testing. When the banks collude by offering a profitable interest rate to the applicants without testing, there is an incentive for each bank to undercut the interest rate in order to get more applicants. In order to generate intertemporal incentives to support the collusion on a high interest rate, banks need to punish each other to prevent deviation in undercutting interest rates, which can be monitored by looking at the loan portfolio size of each bank. However, a high interest rate generates incentives for banks to conduct credit worthiness testing and get higher quality applicants while manipulating the loan portfolio size. To see this, let us look at the following example.

By undercutting the interest rate offered to an applicant without credit worthiness testing, the expected payoff from this loan to the bank is: $\pi = \lambda p_b F + (1 - \lambda) p_g F - 1$. Alternatively, the bank can test the applicant, undercut the interest rate if it is a good type, and undercut the interest rate to another untested applicant if the tested one turns out to be a bad type (this way the bank always gets one applicant for sure); the expected payoff to the bank is $\pi'' = \lambda[\lambda p_b F + (1 - \lambda_g F) - 1] + (1 - \lambda)(p_g F - 1) - c$. The difference between π and π is $\lambda(1 - \lambda)(p_g - p_b)F - c$, which is increasing with F. When there are multiple applicants, while benefiting from finding a good type applicant through a credit worthiness test, a bank will switch to an untested applicant if the tested one turns out to be of bad type, and this substantially

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[14] Banks could play more general mixed strategies. For example, banks could mix between testing n applicants and testing n applicants. We do not delve into these strategies.

improves the net gain from a credit worthiness test. Therefore, when F is high enough, banks will have an incentive to produce information while manipulating the loan portfolio size through interest rates.

Aside from seeing how the repeated game works, the main point is the demonstration that because banks have two ac

$$u_1(0,2) - u_1(1,1) = u_1(1,1) - u_1(2,0),$$

which implies:

$$0.25u_1(0,2) + 0.5u_1(1,1) + 0.25u_1(2,0) = u_1(1,1).$$

Thus with the deviation, the expected continuation payoff remains unchanged. We can show that this result holds with more than two applicants for any Symmetric Perfect Public Equilibrium, as defined in the Appendix; we omit the proof here for brevity.

Therefore, in order to detect banks' deviations through over-production of information, banks' strategies need to depend on the public histories of banks' loan portfolio performances and portfolio sizes. However, the theory does not provide details on how the public histories are linked to banks' beliefs and strategies. To help understand this issue for later empirical tests, again let us consider a simple example with $N = 2$ applicants. Suppose Bank 1 deviates from the equilibrium strategy s (test no applicants, and offer some high interest rate F to both of them) to strategy s as follows: test one applicant; if he is good, offer a loan at rate F_α^-, and reject the other applicant; if the applicant is bad, reject it, and offer a loan to the other applicant at loan rate F_α^-. In this way, the expected loan portfolio size is not changed, but loan performance will be improved; there is less likely to be a default. Given the loan distribution ($D_1 = 1$, $D_2 = 1$), from Bank 2's point of view, without deviation by Bank 1, the probability of Bank 2 having a loan default is:

$$q = \lambda(1 - p_b) + (1 - \lambda)(1 - p_g).$$

With Bank 1 deviating to strategy s, Bank 2's default probability becomes:

$$q' = \lambda(1 - p_b) + (1 - \lambda)[\lambda(1 - p_b) + (1 - \lambda)(1 - p_g)].$$

The likelihood of default is higher by:

$$\Delta q = q' - q = \lambda(1 - \lambda)(p_g - p_b) < 0.$$

To detect a deviation, however, banks should compare their results. That is, they should check their loan performance difference. Given the loan distribution ($D_1 = 1$, $D_2 = 1$), without deviation by Bank 1, the probability of Bank 2 having a worse performance than Bank 1 is:

$$q_r = [\lambda(1 - p_b) + (1 - \lambda)(1 - p_g)][\lambda p_b + (1 - \lambda)p_g] < q.$$

With Bank 1 deviating to strategy s, this probability becomes:

$$q'_r = \lambda(1 - p_b)[\lambda p_b + (1 - \lambda)p_g] + (1 - \lambda)[\lambda(1 - p_b) + (1 - \lambda)(1 - p_g)]p_g.$$

We have:

$$\Delta q_r = q'_r - q_r = \lambda(1 - \lambda)(p_g - p_b) = \Delta q.$$

Therefore, compared with punishing each other after a bad performance, doing that after a relatively bad performance incurs a smaller probability of a mistaken punishment ($q_r < q$), while it generates the same incentive to not to deviate ($q_r = q$). The measure of the "performance

difference" excludes the case where both banks perform poorly, and excluding this case is empirically important because it can result from aggregate shocks, which we do not model.

Before we start our empirical section, let us briefly discuss the link between information production and credit crunches. When each bank tests a subset of the applicant pool, the winner's curse effect may lead the banks to reject all those non-tested applicants. To see this, assume the banks randomly pick $n < N$ applicants for testing, and offers loans to those that pass the test. To simplify the argument, assume that the interest rates offered to non-tested applicants are higher than the one offered to applicants that passed the test. For the non-tested applicants, it is possible that there does not exist a profitable interest rate due to the winner's curse. If a bank offers loans to non-tested applicants, then given an offer is accepted by an applicant, the probability of this non-tested applicant being a bad type is:

$$\theta \equiv \Pr(\text{bad type} \,|\, \text{not tested}) = \frac{\dfrac{n}{N}\lambda + (1 - \dfrac{n}{N})\dfrac{1}{2}\lambda}{\dfrac{n}{N}\lambda + (1 - \dfrac{n}{N})\dfrac{1}{2}} \ .$$

When n is close to N, θ can be very close to 1. When banks conduct credit worthiness testing, lending standards (loosely defined) can affect lending in two ways. First, those applicants that were tested can be rejected if banks find them to be bad types; second, those applicants that were not tested can be rejected if the proportion of applicants that are tested is large. The second "rejected" category might contain some good type applicants. Therefore, some non-tested applicants can not get loans if both banks test a large portion of all applicants. This is a "credit crunch" in which applicants not tested by either bank are denied loans, even if they are in fact good types.

The above discussions lead to our empirical tests in the next section: banks' relative performance is important for the credit cycles, which have significant impact on the economy. In normal periods, banks produce information about borrowers at the optimal level, and they trigger the punishment phase by over-producing information after observing an abnormal difference in loan performance. The over-production of information leads to credit crunches.

There may, of course, be many possible equilibria, including some that resemble the more familiar price wars and no credit worthiness testing. Also, there can exist equilibria in which past performance does not matter. The empirical tests serve to identify the relevant equilibrium from data, as well as test the model.

3. Empirical Tests

In the model banks form beliefs based on public information. While we cannot measure beliefs directly, we can measure the information used to form beliefs. Our measures are proxies for bank beliefs. The empirical strategy we adopt is to focus on one robust prediction that the theory puts forward, namely, that unlike a perfectly competitive lending market, in the imperfectly competitive lending market that we have described, public histories about rival banks should affect the decisions of any given bank. We construct measures of the relative performance histories of banks, variables that are at the root of beliefs and their formation. In particular, changes in beliefs about rival behavior should be a function of bank public performance differences.

In the U.S. the most important public information available about bank performance is the information collected by bank regulatory authorities (the Federal Reserve, Federal Deposit Insurance Corporation, and the Office of the Comptroller of Currency) in the quarterly Call Reports. While publicly-traded banks also file with the Securities and Exchange Commission, the Call Reports provide the detail on specific loan category amounts outstanding, charge-offs, and losses. We construct Performance Difference Indices (PDI) based on the Call Reports that U.S. banks file quarterly bank regulators. These reports are filed by banks within 30 days after the last business day of the quarter, and become public roughly 25 to 30 days later.[16] For that reason, we try to use more than one lag when we analyze the predictive power of certain variables to be constructed based on the Call Reports. Because the reports appear at a quarterly frequency, we analyze data at that frequency.

To parameterize the relative bank performance for our empirical studies, we use the absolute value of performance differences. Taking the absolute value is motivated by the theory. Even if a bank is doing relatively better than its rivals, it knows that if rivals believe that it has deviated then they will increase their information production, causing the better performing bank to also raise its information production. Banks, whether relatively better performing or relatively worse performing, punish simultaneously, resulting in the credit crunch. If banks' beliefs about rivals' actions change based on our parameterization of the public history, then when this measure increases, i.e., when there is a greater dispersion of relative performance, then banks reduce their lending and increase its quality, resulting in fewer loans, lower loss ratios, and reduced profitability in the future. We construct indices of the absolute value of the difference in loan loss ratios and test whether the histories of such variables have predictive power for future lending decisions, loan losses, and bank stock returns. ng

data on credit card lending and re

Credit Cards and Related Plans (RV)," and "Total Loans and Leases, Net (TL)." We construct the following variables for each bank holding company at quarterly level:

$$\text{Credit Card Loan Loss Ratio } (LL) = (CO\text{-}RV)/LS$$

$$\text{Ratio of Credit Card Loans to Total Loans } (LR) = LS/TL.\text{[20]}$$

With respect to macroeconomic data we use quarterly macroeconomic data from the Federal Reserve Bank of St. Louis for the period 1991.I to 2006.III: "Civilian Unemployment Rate, Percent, Seasonally Adjusted (UMP)," "Real Disposable Personal Income, Billions of Chained 1996 Dollars, Seasonally Adjusted Annual Rate (DPI)," "Federal Funds Rate, Averages of Daily Figures, Percent (FFR)."[21]

3.1.2 Pairwise Tests of Rival Banks

We start by looking at banks pairwise. We do this for two reasons. First, it is not known which banks are rivals, and it may be that not all banks are rivals despite the fact that they are all major credit card lenders.[22] Second, we have only 40 quarterly observations for each bank, so examining several banks jointly (including lags of each individual bank's performance) quickly uses up the degrees of freedom. We focus on the largest six bank holding companies, which constantly remain within the top 20 in credit card loan portfolio size during the period 1991.I to 2004.II.[23] These six banks are: JP Morgan Chase, New York, NY (CHAS) (CHAS); Citicorp, New York, NY (CITI); Bank One Corp., Chicago, IL (BONE); Bank of America, Charlotte, NC (BOAM), MBNA Corp., Wilmington, DE (MBNA); and Wachovia Corp., Winston-Salem, NC (WACH).

In general, we run the following regression for each bank holding company i:

$$y_{it} = \alpha_{ij} x_{it} + \beta_{ij} z_{ijt} + \varepsilon_{ijt}, \text{ for } j \neq i , \quad (1)$$

where

$$_{it} = \quad _{it} \text{ or } \quad _{it}, x_{it} = (Const., DPI_t, UMP_t, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4}),$$
$$z_{ijt} = (|\Delta LL_{ijt-1}|, |\Delta LL_{ijt-2}|, |\Delta LL_{ijt-3}|, |\Delta LL_{ijt-4}|),$$

(or lower) loan loss rates than another bank holding companies, we first take out the mean from the loan loss ratio of each bank, and then take the difference to get LL_{ij}. In this way, $|LL_{ij}|$ reflects the relative performance of the two banks.

$|LL_{ij}|$ is the key variable. It is a particular parameterization of the relevant public information: the performance difference. Conditional on the state of the economy and bank holding company I's own past performance, we ask whether bank holding company I's lending decisions depend on the observed absolute value of the differences between it's own past performance and that of its rival, bank holding company j. For each measure of the relative difference in loan performance, we test whether $\gamma = 0$, using a Wald test (chi-squared distribution).

Step 2: We can sample from u_{it}^* in the regressions to generate new LL_{it}^* or LR_{it}^*, using $y_{it}^* = \alpha_i x_{it}^* + u_{it}^*$ This also creates new x_{it}^* and z_{ijt}^* since both variables involve lags of LL_{it} and LL_{jt}.

Step 3: Use y_{it}^*, x_{it}^*, and z_{it}^* from bootstrap to run the pairwise regression in H_1, and calculate the Significant Index SI.

Step 4: Repeat Step 2 to Step 3 100,000 times, and obtain the distribution of SI.

Step 5: Calculate the p-value of SI^*, i.e. $\Pr(SI \quad SI^*)$.

The results of pairwise regression and bootstrap are reported in Table I. We also conduct some robustness checks. In particular, we explore the learning effect, as clarified below.

An alternative explanation is that banks learn about underlying the economic conditions from other banks' loan performance. Perhaps this learning effect is also captured by the $| LL_{ij}|$ variable that we constructed. It would seem that learning should not be based on absolute differences in bank performance, but on the level of other banks' performances as well as the bank's own performance history. To examine this possibility we add lags of LL_j in the regression of Bank i. Therefore, in the regression equation (1), we replace x_{it} with x_{ijt}:

$$x_{ijt} = (C, DPI, UMP, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4}, LL_{jt-1}, LL_{jt-2}, LL_{jt-3}, LL_{jt-4}).$$

The results for learning effect are also reported in Table I.

In Table I, we report the average value of the coefficients on z_{ijt} as well as whether they are jointly significant. Significant negative coefficients are marked by ' ,' and significant positive coefficients are marked by '#.' Most coefficients are negative, which matches the theoretical prediction. When the difference between the loan performance history is large, it leads to (an increase in lending standards and, consequently) a subsequent decrease in (lower quality) loans and a consequent reduction in loan losses. Many negative coefficients are significant (indicated by *** for the 1% level, by ** for the 5% level, and by * for the 10% level, and similarly for positive coefficients). Also, the Significance Indices all have very low p-values in our test using bootstrap.

A literal interpretation of the model would mean that there are two "regimes," rather than a possible large number of levels of intensity of information production. Perhaps there is a threshold effect, in that only if the absolute performance differences reach a certain critical level does (mutual) punishment occur. We estimated such a model using maximum likelihood and the results were not uniformly improved compared to those reported above (and so the results are omitted).

3.1.3 An Aggregate Performance Difference Index

Based on the success of the pairwise tests, we move next to analyzing the histories of all relevant rival credit card lenders jointly. We construct an aggregate Performance Difference Index (PDI):

$$PDI_t = \frac{\sum_{i>j} | LL_{it} - LL_{jt} |}{15} .$$

This Performance Difference Index measures the average difference of the competing banks' loan performances. As the Wachovia series stops at 2001.II, our *PDI* index ends at 2001.II. Again, we first take out the mean from each LL_i, and then take the difference. For each bank *I*, we estimate the following model:

$$y_{it} = \alpha_i x_{it} + \beta_i z_t + \varepsilon_{it}, \ i = 1,...,6, \quad (2)$$

where y_{it} and x_{it} are the same as in regression (1), and $z_t = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$. The coefficients on z_t and their *t*-statistics are reported in Table II.

In a more restrictive environment, we estimate a pooling regression model with the restriction $\beta_i = \beta$ for $I = 1,...,6$. The results are also reported in Table II.

From Panel A and C in Table II, we observe that most coefficients are negative, consistent with our conjecture from the theory. When there is a large performance difference across all the rival banks, banks raise their lending standards to punish each other, and consequently future loan losses and loan ratios go down. In particular, in regressions with $y_{it} = LL_{it}$, the coefficients for JP Morgan Chase, Bank of America, and Wachovia are statistically significant; in regressions with $y_{it} = LR_{it}$, the coefficients for Citicorp, Bank One, and Bank of America are statistically significant. In our pooling regressions, the significance of our Performance Difference Index is improved.

The coefficients are also economically significant. For example, in the regressions with Bank of America, the average coefficients on *PDI* are -0.444 and -0.568, for $y_{it} = LL_{it}$ and $y_{it} = LR_{it}$, respectively. The means of *LL* and *LR* are 0.0237 and 0.0579, respectively. Given that the standard deviation of *PDI* is 0.00454, when *PDI* changes by one standard deviation, *LL* decreases by 0.00202 (9% of the mean), and *LR* decreases by 0.00258 (5% of the mean). For Bank One, which has the largest absolute value in regression coefficients on PDI, the average coefficients on *PDI* for *LL* and *LR* are -0.786 and -3.850. The mean of *LL* and *LR* are 0.0316 and 0.0911. When *PDI* changes by one standard deviation, *LL* decreases by 0.00357 (11% of the mean), and *LR* decreases by 0.0275 (19% of the mean).

3.1.4. Bank Stock Returns and Performance Differences

In a credit crunch banks make fewer loans and spend more on information production, so their profitability declines. In this section, we test that implication of the model. Specifically, we ask whether the Performance Difference Index has predictive power for the stock returns of each top bank holding company in credit card loans. We collect the stock returns from CRSP from 1991.I to 2001.I. We carry out the tests for all six bank holding companies. According to our theory, after observing large performance differences between banks, banks will raise their lending standards (which is costly), and cut lending. Consequently, their profit margins will be lower. Therefore, we expect to see negative loadings on the lags of the *PDI*. Note that this is not an asset pricing model, but a test concerning bank profits, as measured by stock returns. The

variable. Again, robustness is checked by imposing the restriction $\beta_i = \beta$ for $I = 1,\ldots, 6$. All the results are reported in Table III.

From Table III, we see that the PDI from the previous four quarters significantly predicts the stock return for the current quarter, and the results are robust if we include a lag of the dividend yield in the regressions. The average coefficient on the lags of *PDI* from OLS estimates is about -3.5. One standard deviation change in *PDI* (0.00454) leads to an average of 0.0159 in stock returns, or 159 basis points!

3.1.5 Rajan's Reputation Hypothesis

Rajan (1994) argues that reputation considerations of bank managers cause banks to simultaneously raise their lending standards when there is an aggregate shock to the economy causing the loan performance of all banks to deteriorate. Banks tend to neglect their own loan performance history in order to herd or pool with other banks. Rajan's empirical work focuses on seven New England banks over the period 1986-1991. His main finding is that a bank's loan charge-offs-to-assets ratio is significantly related not only to its own loan loss provisions-to-total assets ratio, but also to the average charge-offs-to-assets ratio for other banks (instrumented for by the previous quarter's charge-offs-to-assets ratio).[25] In the context here the question is whether our measure of banks' beliefs about rivals' credit standards, the performance difference index, remains significant in the presence of an average or aggregate credit card loss measure. We construct:

$$\text{Aggregate Credit Card Loan Loss}\,(AGLL_t) = \frac{\sum_i (CO_{it} - RV_{it})}{\sum_i LS_{it}}\ ,$$

and then examine the coefficients on the ags of *AGLL* and *PDI*, separately and jointly, in our regression equation (2) with $z_t = (AGLL_{t-1}, AGLL_{t-2}, AGLL_{t-3}, AGLL_{t-4})$ or $z_t = (AGLL_{t-1}, AGLL_{t-2}, AGLL_{t-3}, AGLL_{t-4}; PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$.

The coefficients on z_t and their *t*-statistics are reported in Table IV, which also show the results with the restriction that the coefficients on z_t are the same across bank holding companies.

Rajan's (1994) hypothesis is that an aggregate bad shock leads banks to raise their standards, so we would expect the coefficients on lags of *AGLL* to be significantly negative. However, as the Table IV shows, with or without *PDI* in the regressions, the coefficients on *AGLL* are mostly positive and significant, with a few exceptions. At the same time, the coefficients on lags of *PDI* remain negatively significant, even after we include lags of *AGLL* in our regression.

3.2 An Aggregate Performance Difference Index for Commercial and Industrial Loans

In this section we extend the empirical analysis in two important ways. First, we go beyond credit card lending at six banks to examine commercial and industrial loan market at an aggregate level, and we probe the implications of the theory for macroeconomic dynamics. Second, we study whether the additional risk brought by the bank strategic collusion/competition on information production is priced in the financial market.

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[25] There are several interpretations of Rajan's result. For example, the charge-offs of other banks may be informative about the state of the economy, so their significance in the regression is not necessarily evidence in favor of Rajan's theory.

3.2.1 VAR Analysis of the Fed's Lending Standards Index

We now turn a different category of loans, commercial and industrial loans. This category covers lending to firms of all sizes and corresponds to the loans at issue when there is a credit crunch. If banks increase their information production, that is, raise their lending standards, then some borrowers are cut off from credit — a credit crunch that should have macroeconomic implications.

In this subsection, we use Vector Autoregressions (VARs) to analyze the aggregate implications of banks' loan performance differences. In contrast to the single equations estimated above, a VAR system of equations lets us control for the feedback between current and past levels of performance differences, the lending standard survey results, and macroeconomic variables. Given estimates of these interactions, we can identify the impact that unpredictable shocks in performance difference public histories have on other variables in the system. We first ask whether the performance difference histories predic

Funds Rate affects loan demand; Commercial Bank C&I Loan is the equilibrium outcome. The *PDI* is hypothesized to capture banks' beliefs, which affects all the other variables. The exogenous variables include a constant and a time trend. We run the VAR for the period of 1990.II—2006.III, which is the longest continuous of period where we have both *STAND* and *PDI* data. During this period of time, the means and standard deviations of these four variables are:

namely, the Performance Difference Index. Moreover, since relatively smaller firms are more dependent on bank loans (see, e.g., Hancock and Wilcox (1998)), we expect that the coefficients on PDI (below, we construct the mimicking portfolio for this factor) are larger for smaller firms.

We adopt the widely-used Fama-French three factor empirical asset pricing model.[29] According to Fama and French, the sensitivity of a firm's expected stock return depends on three factors: the excess return on a broad based market portfolio, r_m-r_f; the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (small minus large), *SMB*; the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (high minus low), *HML*. The model is estimated using quarterly data, as *PDI* can only be calculated quarterly.

We hypothesize that bank stock returns will be sensitive to *PDI* and that *PDI* is not spanned by the other factors. Further, non-financial firms' stock returns will also be sensitive, increasingly so for smaller firms. The monthly firm returns are collected from CRSP (then transformed into quarterly data). We separate out commercial banks and non-financial firms based on their SIC codes, and then divide the non-financial firms into ten deciles based on the capitalizations. The data used are from 1984.I to 2006.IV, during which the performance difference index is available.

One concern regarding *PDI* as a macro factor is that it might have been priced into the three factors.   To address that concern, we first regress the three Fama-French factors on the performance difference index to see whether there is a significant correlation between them. The results are as follows:

	Coefficient on PDI	t-statistics
r_m-r_f	-238.90	-0.90
SMB	-49.79	-0.29
HML	-6.98	-0.03

We can see that none of the coefficients are significant. Therefore, *PDI* is not spanned by the other factors.

As is standard in the asset pricing literature, we proceed by first constructing the mimicking portfolio for our macro factor, *PDI*. Mimicking portfolios are needed to identify the factor risk premiums when the factors are not traded assets. The risk premium is constructed as a "mimicking portfolio" return whose conditional expectation is an estimate of the risk premium or price of risk for that factor. We then use a time series regression approach, as in, for example, Breeden, Gibbons, and Litzenberger (1989), with the book-to-market sorted portfolios as the base assets. A recent study by Asgharian (2006) argues that this approach is the best for constructing mimicking portfolios for factors for which a time-series factor realization is available.

We first regress the *PDI* factor on the excess returns of the ten book-to-market sorted portfolios (either equal-weighted or value-weighted), and then construct the mimicking portfolio with the weight of each portfolio proportional to the regression coefficient on the excess return of this portfolio. Specifically, we first run the following regression:

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[29] See Fama and French (1993, 1996). Carhart (1997) introduced an additional factor, the momentum factor. The results with additional momentum factor are basically the same, thus omitted. We collect the quarterly Fama-French three factors from French website (the construction method can also be found there). The risk free rates are three-month T-Bill rates (secondary market rates) from FRED II (we use the rate of the first month in each quarter) at Federal Reserve Bank at St. Louis.

$$PDI_t = \lambda_0 + \sum_{i=1}^{10} \lambda_i R_{it} + \varepsilon_t \ ,$$

where R_{it} is the excess return on the base asset I at time t. The weights are constructed as follows:

$$w_i = \frac{\lambda_i}{\displaystyle\sum_{i=1}^{10} \lambda_i} \ ,$$

and the excess return on the mimicking portfolio is given by:

$$R_{PDI,t} = \sum_{i=1}^{10} w_i R_{it} \ .$$

According to Breeden et al. (1989), the asset betas measured relative to the maximum correlation portfolio are proportional to the betas measured using the true factor.

After we form the mimicking portfolio, we add it to the Fama-French three-factor model. The results are reported in Table VII.

The results in Table VII show that the PDI mimicking portfolio is a significant risk factor for small non-financial firms but not for banks or large non-financial firms. Note that the coefficients on R_{PDI} for smaller firms are larger, thus confirming our conjectures. The standard deviation of R_{PDI} (constructed with value-weighted book-to-market portfolios) is 72 percent (this is quite large because the mimicking portfolio involves short positions). Therefore, when R_{PDI} changes by one standard deviation, the excess return for smallest non-financial firms changes by about 150 basis points! We conclude that the competition and collusion among banks is an important risk factor for stock returns, especially for small non-financial firms. The size effect further demonstrates that the Performance Difference Index we constructed is not capturing some sort of learning effect about macroeconomic condition, which would be spanned by the other risk factors.

As a robustness check, we also add the mimicking portfolio to the classic CAPM model. The results are reported in Table VIII.

The results in Table VIII are quite similar to those in Table VII. The magnitude of the coefficients on R_{PDI} is about the same as in Table VII, and this shows that without *SML* or *HML* in the regression, the *PDI* factor does not pick up higher loadings. This confirms that *PDI* risk factor represents an independent source risk which cannot be spanned by *SML* or *HML*.

4. Conclusion

 An important message of Green and Porter (1984) is that collusion can be very subtle. The subsequent theoretical work is very elegant and powerful. See Abreu, Pearce, and Stacchetti (1990) and Fudenberg, Levine, and Maskin (1994). Empirical work on testing models of repeated games, however, has been difficult because of the data requirements for estimation of structural models. Empirical work has been limited and has focused on price wars as the only examples of such imperfect competition. We presented a theoretical model of a repeated lending game, in which banks compete in a rather special way, via the intensity of information production. We then empirically tested the model by parameterizing the information on which banks' beliefs are based. The Performance Difference Indices are proxies for banks' beliefs.

We studied banking, an industry in which there have not been price wars. Banking is an industry with limited entry; it is a highly concentrated industry, and it is an industry that is informationally

opaque and hence regulated. Banks produce private information about their borrowers, but they do not know how much information rival banks are producing. The information opaqueness affects competition for borrowers in that rivals can produce information with different precision. This causes the imperfect com

A. Formalization of the Stage Strategy

Bank i randomly chooses n_i applicants to test. For those applicants that bank i does not test, it will decide to approve applications to $N_{\alpha i}$ N-n_i of the applicants, and offer the approved applicants a loan at interest rate $F_{\alpha i}$. The bank rejects the rest of the non-tested applicants. For those applicants that are tested by bank i, the bank will observe a number of good type applicants, N_{gi} n_i, and will then decide to approve applications to $N_{\beta i}$ N_{gi} of the applicants that passed the test, and offer the approved applicants a loan at interest rate $F_{\beta i}$. Bank i can also decide to approve applications to $N_{\gamma i}$ n_i-N_{gi} of the applicants that failed the test, and offer these approved applicants a loan at interest rate $F_{\gamma i}$. The bank rejects the remaining applicants. In general, $F_{\alpha i}$, $F_{\beta i}$ and $F_{\gamma i}$ could vary among the corresponding category of applicants, that is, different applicants in the same category could possibly get offers of loans at different interest rates. Therefore, we interpret $F_{\alpha i}$, $F_{\beta i}$ and $F_{\gamma i}$ as vectors of interest rates charged to those approved non-tested applicants. The stage strategy of a bank is:

$$s_i = \{n_i, N_\alpha(n_i, N_{gi}), N_\beta(n_i, N_{gi}), N_{\gamma i}(n_i, N_{gi}), F_{\alpha i}(n_i, N_{gi}), F_{\beta i}(n_i, N_{gi}), F_{\gamma i}(n_i, N_{gi})\},$$

where:

n_i: the number of applicants that bank i tests;
N_{gi}: the number of good applicants found by bank i with the test;
$N_{\alpha i}$: the number of applicants that bank i offers loans to without test;
$N_{\beta i}$: the number of applicants that pass the test and get a loan from bank i;
$N_{\gamma i}$: the number of applicants that fail the test and get a loan from bank i;
$F_{\alpha i}$: the interest rate on the loan that bank i offers to the applicants without a test;
$F_{\beta i}$: the interest rate on the loan that bank i offers to the applicants that pass the test;
$F_{\gamma i}$: the interest rate on the loan that bank i offers to the applicants that fail the test.

B. Proof of Proposition 1

We first prove the following lemma.

Lemma 1 *If it exists, in any symmetric stage Nash equilibrium in which neither bank conducts credit worthiness testing, each bank offers loans to all the loan applicants at the same interest rate.*

Proof. It is easy to check that if bank i is playing $s_i = (n_i = 0, N_{\alpha i} < N, F_{\alpha i})$, then bank $-i$ can strictly increase its profits by playing $s'_{-i} = (n_{-i} = 0, N'_{\alpha-i} = N, F'_{\alpha-i})$, where the strategy s_{-i} is to offer $F'_{\alpha-i} = F_{\alpha i}$ to $N_{\alpha i}$ applicants (although these $N_{\alpha i}$ applicants might not be the same applicants that bank i is offering loans to), and offer X to the rest of them. Let F^* be the interest rate corresponding to zero profits in the loan market when there is no testing. Then:

$$E\pi_i = \frac{N}{2}[\lambda p_b F^* + (1-\lambda)p_g F^* - 1] = 0,$$

$$\text{and } F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g} < X \text{ (by Assumption 1)}.$$

Assume bank i is playing $s_i = (n_i = 0, N_{\alpha i} < N, F_{\alpha i})$, with $F_{\alpha i} = (F_1, F_2, ..., F_N)$. Suppose F_j F^* for j = 1, 2, ..., N and assume there exist j and k, such that F_j F_k, and, without loss of generality, F_k F^*. Bank $-i$ can strictly increase its profitability by playing

$s'_{-i} = (n_{-i} = 0, N'_{\alpha-i} = N, F'_{\alpha-i})$, where $F_{\alpha i} = (F_1,...,F_{k-1}, F_k^-, F_{k+1},...,F_N)$ and F_k is smaller than F_k by an infinitely small amount. Therefore, interest rates are bid down until each bank offers F^* to all the applicants.

Proof Proposition 1: From Lemma 1, we see that in a symmetric equilibrium with no bank testing applicants, both banks offer loans to all the applicants at $F^* = \dfrac{1}{\lambda p_b + (1-\lambda)p_g} < X$ (by

Assumption 1). With $c < \dfrac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$, a bank will have an incentive to conduct credit worthiness testing on at least one loan applicant and to offer loans to those applicants that pass the test, offering an interest rate F^{**}, which is lower than F^* by an infinitely small amount. To see this consider a bank that deviates by conducting credit worthiness testing on one applicant. The expected profit from this deviation is:

$$E\pi_i^d = (1-\lambda)(p_g F^* - 1) - c.$$

We have:

$$E\pi_i^d > 0 \text{ iff } c < (1-\lambda)(p_g F^* - 1) = \frac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}.$$

We can see that if $c \geq \dfrac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$, then F^* will be a Nash equilibrium interest rate on the loan, and no bank will conduct credit worthiness testing.

C. Proof of Proposition 2

We first prove the following three lemmas.

Lemma 2 *In any symmetric stage Nash equilibrium in which both banks test all the applicants, each bank offers loans to all the applicants that pass the test at the same interest rate.*
   The proof is similar to **Lemma 1** and is omitted.

Lemma 3 *If it exists, in any symmetric stage Nash equilibrium in which both banks test $n < N$ applicants, each bank offers loans to all applicants that pass the test (good types) at $F^{**} = \dfrac{1}{p_g}$.*

   The proof is similar to **Lemma 1** and is omitted.

Lemma 4 *If it exits, in any symmetric stage Nash equilibrium in which both banks test $n < N$ applicants, each bank either offers loans to all non-tested applicants at the same interest rate or offers loans to none of them.*

Proof. If there exists a feasible F X such that the banks can make a strictly positive profit by lending to non-tested applicants at F, following a similar argument as in the proof of Lemma 1, we conclude that each bank offers loans to all non-tested applicants at the same interest rate. If there does not exist a feasible F such that the banks can make a non-negative profit by lending to

non-tested applicants at F, we conclude that each bank offers loans to none of those non-tested applicants.[30]

Proof Proposition 2: The proof is by contradiction. If in equilibrium both banks conducting credit worthiness testing on all the applicants, from Lemma 2, both banks offer loans to all the applicants that pass the test, i.e., $N_\beta = N_g$, where N_g denotes the number of applicants passing the test. Banks will make no loans to bad types found by testing, that is, $N_\gamma = 0$. Both banks use the credit worthiness test at a cost c per applicant. Assume the loan interest rate they charge to approved applicants is $F_\beta(N,N_g)$, depending on N_g. Each bank must earn non-negative expected profits $E\pi \geq 0$, i.e., the participation constraints. For each realization of N_g, each bank expects to make loans to $N_g/2$ applicants. Let p_k denote the probability of finding k good type applicants. Then:

$$E\pi_i = E\sum_{k=0}^{N}\frac{1}{2}kp_k[\,p_g F_\beta(N,k)-1]-Nc \geq 0.$$

Assume now, if bank i cuts F_β by an infinitely small amount, that is, $F_\beta^d(N_g) = F_\beta^-(N_g)$, , then it will loan to N_g applicants for any realization of N_g. We have:

$$E\pi_i^d = E\sum_{k=0}^{N}kp_k[\,p_g F_\beta^-(N,k)-1]-Nc \geq E\pi_i.$$

For the case in which both banks conducting credit worthiness testing on a subset of the applicants, if the banks offer loans all non-tested applicants, we have $F_\beta = F^{**}$ and $F_\alpha = F(n)$, which are the interest rate that results in zero expected profit from offering loans to tested good type applicants and non-tested applicants when banks test n applicants. It is easy to check that $F(n) > F^{**}$. The argument for $F_\alpha = F(n)$ is similar to the argument for $F_\beta = F^{**}$. However, at $F_\alpha = F(n)$ and $F_\beta = F^{**}$, banks will earn negative expected profit due to the test cost. If the banks offer loans to none of the non-tested applicants, the banks will only offer loans to those applicants that passed the test at F^{**}. The argument is similar.

D. Formalization of the Repeated Game

Assume that the two banks play the lending market stage game period after period, each with the objective of maximizing its expected discounted stream of profits. Upon entering a period of play, a bank observes only the history of:
     (i) its own use of the credit worthiness test and the results;
     (ii) its own interest rate on the loan offered to applicants;
     (iii) its own choice of applicants that it lent to;
     (iv) its own and its competitor's loan portfolio size (number of loans made);
     (v) its own and its competitor's number of successful loans.

For bank i, a full path play is an infinite sequence of stage strategies. The infinite sequence $\{s_{it}\}_{t=0}^{\infty}$, $i=1,2$, together with nature's realization of the number of good type applicants and the applicants' rational choice of bank, implies a realized sequence of loans from bank i, as well as a quality of the borrowers who received loans from bank i. That is:

$$K_{it} = (D_{\alpha it}, D_{\beta it}, D_{\gamma it}, \chi_{\alpha it}, \chi_{\beta it}, \chi_{\gamma it}),$$

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[30] Here we neglect a non-generic case in which there exists an F such that the banks can earn zero profit by offering loans to a non-tested applicant, and there does NOT exist an F such that the banks can earn strictly positive profit by offering loans to a non-tested applicant. In this case, each bank can possibly offer to a subset of the non-tested applicants. However, including this case will not affect the results in Proposition 1.

where D denotes the number of applicants that accepted the offer, and χ denotes the number of successful borrowers; α, β, and γ denote the corresponding category, as defined earlier (α untested, approved, applicants; β tested, good types, approved; γ tested, bad types, approved). Define:

$$D_{it} = D_{\alpha it} + D_{\beta it} + D_{\gamma it}$$

$$\chi_{it} = \chi_{\alpha it} + \chi_{\beta it} + \chi_{\gamma it}.$$

Let the public information at the start of period $t+1$, be $\kappa_t = (\kappa_{1t}, \kappa_{2t})$, where $\kappa_{it} = \{D_{it}, \chi_{it}\}$, $i=1,2$ (for each bank). So, the information set includes the realization of the number of loans made by bank i and the number of borrowers that repaid their loans in period t.

At the beginning of period T bank i has an information set: ,

where   is the action of bank i (by convention   ).

A (pure) strategy for bank i associates a schedu97.25284 608.639629922 4s9y10.9922 0 0 10.9922 304.0841

According to the definition, the stage game strategies are the same, but the continuation strategies can differ. In particular, note that the continuation value functions for Bank 1 and Bank 2 are symmetric in that if we exchange the loan portfolio sizes and loan performances, the continuation values will also be exchanged. In such an SPPE, the expected payoff for the two banks are the same, but asymmetric play is allowed after the first period, for asymmetric realizations of loan portfolio size and loan performance.

Lemma 5 *In a Symmetric Perfect Public Equilibrium, if on the equilibrium path, banks make offers to all loan applicants without credit worthiness test at an interest rate higher than*

$$F^* = \frac{1}{\lambda p_b + (1-\lambda) p_g},$$ *and the continuation payoffs only depend on loan portfolio distribution*

(D_1, D_2), then for any value of D we have:

$$\delta u_i(D, N-D) - \delta u_i(D+1, N-D-1) = [\lambda p_b + (1-\lambda) p_g] F_\alpha - 1.$$

Proof: Assume that there exists a SPPE with $s = (n = 0, N_\alpha = N, F_\alpha)$ played on the equilibrium path, where F_α is a constant larger than $F^* = \dfrac{1}{\lambda p_b + (1-\lambda) p_g}$, and the continuation value function does not depend on (χ_1, χ_2), which are the numbers of defaulted loans in banks' loan portfolios. To eliminate the incentive for a bank i to deviate to strategy $s'(D) = (n = 0, N_\alpha = D, F_\alpha^-)$ with $0 \le D \le N$, for any $D \le D'$, we must have:

$$\pi_i(s'(D), s) + \delta u_i(D, N-D) = \pi_i(s'(D'), s) + \delta u_i(D', N-D'),$$

which implies:

$$\delta u_i(D, N-D) - \delta u_i(D+1, N-D-1) = \pi_i(s'(D+1), s) - \pi_i(s'(D), s).$$

The result is immediate. Intuitively, the expected payoff with no deviation is a linear combination of the expected payoffs with deviations in the form of $s'(D)$, D=0,1,...,N. Therefore, the expected payoff for each deviation with $s'(D)$ must be the same.

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Table I: This table contains the results for pairwise regressions. In Panel A and C, for each pair of banks, we run the regression: $y_{it} = \alpha_{ij}x_{it}+\beta_{ij}z_{ijt}+\varepsilon_{ijt}$, with $y_{it} = LL_{it}$ or LR_{it}, $x_{it} = (C, UMP, DPI, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4})$ and $z_{ijt} = (|\ LL_{it-1}|, |\ LL_{it-2}|, |\ LL_{it-3}|, |\ LL_{it-4}|)$. In Panel B and D, for each pair of banks, we run the regression: $y_{it} = \alpha_{ij}x_{ijt}+\beta_{ij}z_{ijt}+\varepsilon_{ijt}$, with $y_{it} = LL_{it}$ or LR_{it}, $x_{it} = (C, UMP, DPI, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4}, LL_{jt-1}, LL_{jt-2}, LL_{jt-3}, LL_{jt-4})$ and $z_{ijt} = (|\ LL_{it-1}|, |\ LL_{it-2}|, |\ LL_{it-3}|, |\ LL_{it-4}|)$. We report the average coefficients on z_{ijt} for each pair of banks as well as the Wald-test for the significance of these coefficients. We mark each significant average coefficient with '*' or '#' depending on the sign of the average coefficient: '*' for negative sign and '#' for positive sign. The number of '*' or '#' indicates the level of significance: three for p-value ≤ 0.01, two for 0.05, one for 0.10.

	Panel A						Panel B					
$y_{it} = LL_{it}$	CHAS	CITI	BONE	BOAM	MBNA	WACH	CHAS	CITI	BONE	BOAM	MBNA	WACH
CHAS		-0.583 ***	0.064	0.044	-0.061 **	-0.446 ****		-0.641 ***	0.030	0.029	0.010	-0.231
CITI	-0.175		-0.066	0.063	-0.010	-0.209 ****	-0.278 **		-0.122 *	0.064	0.009	-0.195 ***
BONE	-0.036	-0.246 ***		-0.228	-0.387 **	-0.302 ***	-0.119 *	-0.299 ***		-0.183	-0.519 ***	-0.380 **
BOAM	0.307 ##	-0.127	-0.081		-0.173	0.022 ##	0.248 #	-0.113 ***	-0.087		-0.268	0.062
MBNA	0.117	-0.023	0.043	-0.054		-0.161 ***	0.153 ##	-0.053 **	-0.046 ***	-0.183 **		-0.090 **
WACH	-0.051	-0.115 ***	-0.185 *	0.096	-0.241 ***		-0.061	-0.111 ***	-0.155 ***	0.029	-0.195	

Significance Index: 39			Bootstrap P-Value: 0.00079			Significance Index: 45			Bootstrap P-Value: 0.00001		

	Panel C						Panel D					
$y_{it} = LR_{it}$	CHAS	CITI	BONE	BOAM	MBNA	WACH	CHAS	CITI	BONE	BOAM	MBNA	WACH
CHAS		-0.574 **	-0.077	-0.259 **	0.419	-0.010 ***		-0.522	-0.078	-0.405 ***	0.496	-0.186
CITI	0.646		-0.590 ***	-0.572 ***	-0.224	-0.327 ***	-0.074		-0.630 ***	-0.615 ***	-0.075	-0.351 *
BONE	-0.375	-0.652 ***		-1.187 ***	-0.875	-1.316 **	-0.379	-0.885 ***		-1.184 ***	-1.117	-1.355
BOAM	-0.228	-0.497 ***	-0.184		-0.959 ***	-0.115 ***	-0.201	-0.350 ***	0.139		-0.742 ***	-0.080
MBNA	-0.131	0.440	0.956	0.990 ##		0.900 ###	-1.515	-0.750	1.392 ###	1.324 ##		0.961 #
WACH												

Table II: This table contains the results for Performance Difference Index (PDI) regressions. In Panel A and C, for each bank, we run the regression: $y_{it} = \alpha_i x_{it} + \beta_i z_t + \varepsilon_{it}$, with $y_{it} = LL_{it}$ or LR_{it}, $x_{it} = (C, UMP, DPI, LL_{it\text{-}1}, LL_{it\text{-}2}, LL_{it\text{-}3}, LL_{it\text{-}4})$ and $z_t = (PDI_{t\text{-}1}, PDI_{t\text{-}2}, PDI_{t\text{-}3}, PDI_{t\text{-}4})$. In Panel B and D, we pool the data of six banks together and estimate the system with the restriction that β_is are the same across banks: $y_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$, with $y_{it} = LL_{it}$ or LR_{it}, $x_{it} = (C, UMP, DPI, LL_{it\text{-}1}, LL_{it\text{-}2}, LL_{it\text{-}3}, LL_{it\text{-}4})$ and $z_t = (PDI_{t\text{-}1}, PDI_{t\text{-}2}, PDI_{t\text{-}3}, PDI_{t\text{-}4})$ for $i = 1,\ldots,6$. The system is estimated using Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) methods. We report the coefficients on z_t as well as their t-statistics.

	Panel A												Panel B: Pooled			
	CHAS		CITI		BONE		BOAM		MBNA		WACH		OLS		SUR	
$y_{it} = LL_{it}$	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$PDI_{t\text{-}1}$	-0.942	-2.10	-0.279	-0.50	-1.392	-1.42	-1.380	-2.48	-0.089	-0.47	-0.679	-3.13	-0.818	-4.30	-0.563	-4.38
$PDI_{t\text{-}2}$	0.039	0.09	0.140	0.27	-0.786	-0.81	-0.040	-0.07	0.080	0.41	-0.393	-1.65	-0.169	-0.88	-0.202	-1.51
$PDI_{t\text{-}3}$	0.161	0.35	0.161	0.31	0.135	0.14	0.099	0.17	-0.005	-0.03	-0.048	-0.20	-0.028	-0.14	-0.017	-0.13
$PDI_{t\text{-}4}$	-0.098	-0.22	-0.117	-0.24	-1.100	-1.19	-0.453	-0.75	0.095	0.53	-0.546	-2.31	-0.341	-1.81	-0.036	-0.27
R^2	0.77		0.75		0.83		0.71		0.88		0.83					

	Panel C												Panel D: Pooled			
	CHAS		CITI		BONE		BOAM		MBNA		WACH		OLS		SUR	
$y_{it} = LR_{it}$	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$PDI_{t\text{-}1}$	0.144	0.30	-1.746	-2.48	-1.880	-0.78	-0.710	-2.45	0.616	0.52	0.933	0.12	-0.535	-1.32	-0.403	-2.23
$PDI_{t\text{-}2}$	-0.068	-0.14	-1.407	-2.16	-3.784	-1.58	-0.386	-1.33	-0.353	-0.29	-0.498	-0.58	-0.823	-2.02	-0.578	-3.19
$PDI_{t\text{-}3}$	-0.214	-0.44	-1.557	-2.40	-3.826	-1.61	-0.315	-1.04	-0.697	-0.57	-0.727	-0.83	-1.149	-2.79	-0.665	-3.57
$PDI_{t\text{-}4}$	0.187	0.39	-1.579	-2.60	-5.909	-2.61	-0.862	-2.74	1.030	0.92	-0.578	-0.67	-0.932	-2.32	-0.741	-4.02
R^2	0.74		0.89		0.75		0.92		0.88		0.83					

Table III: This table contains the results for the predictive power of Performance Difference Index (PDI) for stock returns. In Panel A and C, for each bank, we run the regression: $r_{it} = \alpha_i x_{it} + \beta_i z_t + \varepsilon_{it}$, with $x_{it} = C$ or $(C, Dividend\ Yield_{it-1})$ and $z_{it} = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$. In Panel B and D, we pool the data of six banks together and estimate the system with the restriction that β_is are the same across banks: $r_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$, for $i = 1,\ldots, 6$. The system is estimated using Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) methods. We report the coefficients on z_t as well as their t-statistics.

Without Dividend Yield	Panel A												Panel B: Pooling			
	CHAS		CITI		BONE		BOAM		MBNA		WACH		OLS		SUR	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
PDI_{t-1}	-3.66	-0.75	3.53	0.66	1.46	0.39	1.35	0.36	-8.28	-1.60	-1.66	-0.48	-1.21	-0.68	-0.82	-0.32
PDI_{t-2}	-2.56	-0.53	-1.73	-0.32	-2.53	-0.67	-3.09	-0.82	1.56	0.30	-6.76	-1.95	-2.50	-1.40	-3.77	-1.48
PDI_{t-3}	-9.78	-2.02	-4.80	-0.90	-8.91	-2.37	-9.97	-2.63	-6.87	-1.33	2.00	0.57	-6.45	-3.59	-4.66	-1.83
PDI_{t-4}	-1.60	-0.32	-4.97	-0.91	-7.13	-1.86	-5.91	-1.53	-4.71	-0.90	-5.80	-1.65	-5.04	-2.77	-6.24	-2.41
R^2	0.13		0.07		0.14		0.25		0.13		0.16					

With Dividend Yield	Panel C												Panel D: Pooling			
	CHAS		CITI		BONE		BOAM		MBNA		WACH		OLS		SUR	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
PDI_{t-1}	-2.72	-0.54	4.62	0.80	4.38	1.28	1.13	0.29	-8.20	-1.56	-2.71	-0.74	-0.83	-0.45	-0.69	-0.28
PDI_{t-2}	-1.65	-0.33	-1.97	-0.36	-0.66	-0.20	-3.20	-0.84	1.65	0.31	-6.96	-2.00	-2.15	-1.20	-3.48	-1.41

Table IV: This table contains the results of testing Rajan's (1994) reputation hypothesis. In Panel A and C, we pool the data of six banks together and estimate the system: $y_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$, with $y_{it} = LL_{it}$ or LR_{it}, $x_{it} = (C, UMP, DPI, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4})$ and $z_t = (AGLL_{t-1}, AGLL_{t-2}, AGLL_{t-3}, AGLL_{t-4})$ for $i = 1,\ldots, 6$. In Panel B and D, we pool the data of six banks together and estimate the system: $y_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$, with

Table VI: This table reports the results of forecasting errors and their variance decomposition among four endogenous variables. For each panel, the first column lists the number of quarters for forecasting, the second column contains the standard errors of forecasting errors for certain forecasting horizon, and the next four columns are the weight (in percentage) of each endogenous variable in contributing to the forecasting errors.

Variance Decomposition of STAND:

Period	St. Error	STAND	PDI	FFR	LOGLOAN
1	6.64	100.0	0.0	0.0	0.0
3	8.03	89.5	2.9	6.9	0.8
5	9.53	65.6	2.7	27.7	4.0
10	11.13	50.0	13.6	32.6	3.8
15	12.49	45.4	18.0	33.3	3.3

Variance Decomposition of PDI:

Period	St. Error	STAND	PDI	FFR	LOGLOAN
1	0.00094	0.2	99.8	0.0	0.0
3	0.00101	6.0	86.2	4.8	3.0
5	0.00134	14.5	76.6	6.5	2.4
10	0.00170	14.7	57.5	24.2	3.6
15	0.00188	14.1	58.6	23.2	4.1

Variance Decomposition of FFR:

Period	St. Error	STAND	PDI	FFR	LOGLOAN
1	0.231	10.7	4.7	84.6	0.0
3	0.527	10.6	12.5	76.1	0.8
5	0.692	13.9	21.3	64.2	0.5
10	0.869	12.9	27.2	57.6	2.3
15	1.017	11.6	20.7	65.2	2.6

Variance Decomposition of LOGLOAN:

Period	St. Error	STAND	PDI	FFR	LOGLOAN
1	0.0050	23.8	0.5	8.1	67.7
3	0.0131	6.6	17.9	51.8	23.7
5	0.0212	14.1	34.6	40.8	10.5
10	0.0363	23.5	50.7	21.7	4.1
15	0.0519	25.1	32.4	39.0	3.5

Table VII: This table reports the results from estimating the augmented Fama-French three factor model:

$$r_i - r_f = \alpha + \beta_1(r_m - r_f) + \beta_2 SMB + \beta_3 HML + \beta_4 R_{PDI} + \varepsilon,$$

where R_{PDI} is constructed from ten book-to-market portfolios, either equal weighted or value weighted. We report the coefficients and their t-statistics (in parentheses).

	α	$r_m\text{-}r_f$	SMB	HML	R_{PDI}	R^2	α	$r_m\text{-}r_f$	SMB	HML	R_{PDI}	R^2
	Commercial Banks (using equal weighted R_{PDI})						Commercial Banks (using value weighted R_{PDI})					
Coefficient	1.556	1.163	-0.070	0.464	0.021	0.72	1.628	1.173	-0.041	0.488	0.000	0.72
(t-stat)	(2.54)	(13.27)	(-0.54)	(4.67)	(0.95)		(2.65)	(12.52)	(-0.33)	(4.88)	(0.01)	
	Non-Finanical Firms (using equal weighted R_{PDI})						Non-Finanical Firms (using value weighted R_{PDI})					
Decile 1	4.940	0.629	1.657	-0.042	0.192	0.65	5.146	0.518	1.983	0.020	0.208	0.61
(Small)	(4.08)	(3.63)	(6.53)	(-0.21)	(4.37)		(4.04)	(2.67)	(7.60)	(0.10)	(2.96)	
Decile 2	-0.398	0.766	1.517	0.108	0.126	0.79	-0.256	0.696	1.731	0.151	0.134	0.76
	(-0.50)	(6.76)	(9.15)	(0.84)	(4.41)		(-0.31)	(5.47)	(10.13)	(1.11)	(2.90)	
Decile 3	-0.534	0.867	1.445	0.093	0.078	0.86	-0.495	0.802	1.585	0.103	0.105	0.85
	(-0.89)	(10.04)	(11.44)	(0.95)	(3.57)		(-0.81)	(8.59)	(12.64)	(1.03)	(3.11)	
Decile 4	-0.702	0.946	1.370	0.160	0.065	0.88	-0.649	0.901	1.483	0.175	0.078	0.88
	(-1.31)	(12.28)	(12.15)	(1.83)	(3.34)		(-1.18)	(10.74)	(13.16)	(1.96)	(2.58)	
Decile 5	-0.120	1.014	1.284	0.126	0.049	0.91	-0.049	0.994	1.364	0.148	0.044	0.91
	(-0.27)	(15.80)	(13.68)	(1.73)	(3.01)		(-0.11)	(14.10)	(14.41)	(1.97)	(1.75)	
Decile 6	0.287	1.005	1.322	0.054	0.011	0.95	0.270	0.985	1.346	0.047	0.026	0.95
	(0.90)	(20.90)	(19.68)	(1.03)	(0.97)		(0.85)	(20.33)	(20.66)	(0.91)	(1.46)	
Decile 7	0.604	1.081	1.063	0.033	-0.004	0.97	0.588	1.077	1.059	0.027	0.001	0.97
	(2.57)	(32.08)	(21.57) 1	(0.86)	(-0.43)		(2.50)	(30.05)	(21.99			

Table VIII