Bank Credit Cycles*

(Preliminary)

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Abstract

Banks produce private information about prospective borrowers. But, in the lending market banks compete with each other without knowing how much information is being produced by rival lenders. We show that strategic interaction between banks results in endogenous credit cycles, with periodic "credit crunches." Banks can create winner's curse problems for rivals by adjusting their credit standards (amount of information produced), sometimes raising standards resulting in some borrowers being unable to obtain credit (a "credit crunch"). This can occur without any change in the macroeconomic environment. We then provide a variety of empirical evidence that this strategic interaction is an important part of business cycle dynamics and is a priced factor in bank stock returns.

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1 Introduction

Changes in bank credit allocation, "credit crunches," are an important part of macroeconomic dynamics. Rather than change the price of loans, banks sometimes ration credit.[1] In this paper we show how the amount of information that banks produce about potential borrowers, and the amount of credit banks are willing to extend, varies through time due to strategic interaction between competing banks. Swings between high and low credit allocations are an inherent part of banking due to the way banks compete for borrowers. Small shocks can lead to prolonged credit crunches. But, bank credit cycles can occur without any change in the macroeconomic environment. We investigate this amplification mechanism and provide empirical evidence that bank credit cycles are an important autonomous part of business cycle dynamics. Also, we show that credit cycles are a priced factor in an asset pricing model of bank stock returns. The theory and evidence are also consistent with many stylized facts about bank lending. For example, the fact that bank lending is procyclical.[2]

The amount of credit banks are willing to extend varies through time. A dramatic example in the U.S. is the period shortly after the Basle Accord was agreed in 1988, during which time the share of U.S. total bank assets composed of commercial and industrial loans fell from about 22.5 percent in 1989 to less than 16 percent in 1994. At the same time, the share of assets invested in government securities increased from just over 15 percent to almost 25 percent. See Keeton (1994) and Furfine (2001).[3] More generally, it has been noted that banks vary their lending standards or credit standards. Bank "lending standards" or "credit standards" are the criteria by which banks determine and rank loan applicants' risks of loss due to default, and according to which a bank then makes its lending decisions. While not observable, there is a variety of evidence showing that while lending rates are sticky, banks do, in fact, change their lending standards. The most direct evidence comes from the Federal Reserve System's Senior Loan Officer Opinion Survey on Bank Lending Practices.[4] 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."[5] Lown and Morgan (2001) 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).

[1] Bank loan rates are sticky. Berger and Udell (1992) regress loan rate premiums against open market rates and control variables and find evidence of "stickiness." (Also, see Berger and Udell (1992) for references to the prior literature.) With respect to credit card rates, in particular, Ausubel (1991) has also argued that they are "exceptionally sticky relative to the cost of funds" (p. 50).

[2] See Lown, Morgan and Rohatgi (2000), Jordan, Peek, and Rosengren (2002), and Lown and Morgan (2002).

[3] This episode is the focus of the empirical literature on credit crunches, an inconclusive literature no doubt due in large part to a fundamental identification problem. See Bernanke and Lown (1991), Hall (1993), Berger and Udell (1994), Haubrich and Wachtel (1993), Hancock and Wilcox (1994), Brinkman and Horvitz (1995), Peek and Rosengren (1995), and Beatty and Gron (2001). Gorton and Winton (2002) provide a brief survey of the credit crunch literature.

[4] The survey is conducted quarterly and covers major banks from all parts of the U.S., accounting for between 60 and 70 percent of commercial and industrial loans in the U.S. The Federal Reserve System's "Senior Loan Officer Opinion Survey on Bank Lending Practices" was initiated in 1964, but results were only made public starting in 1967. Between 1984:1 and 1990:1 the question concerning lending standards was dropped. See Schreft and Owens (1991). Current survey results are available at <http://www.federalreserve.gov/boarddocs/SnLoanSurvey/>.

[5] Lown and Morgan (2001, 2002), Lown, Morgan and Rohatgi (2000), and Schreft and Owens (1991) have analyzed the time series of survey responses to the Senior Loan Officer Opinion Survey on Bank Lending Practices.

Changes in lending standards have macroeconomic implications. Asea and Blomberg (1998) estimate the joint relationship between bank lending standards and unemployment, concluding that cycles in bank lending standards are important in explaining aggregate economic activity. Lown and Morgan (2001) go further. They note that changes in bank lending standards may be responses to loan officers' perceptions of the future macroeconomy, so they adopt the approach that lending standards are endogenous in a standard vector autoregression that controls for current macroeconomic, monetary, and credit conditions. Lown, Morgan and Rohatgi (2000) summarize the results as follows: "A shock to credit standards and its aftermath very much resemble a 'credit crunch.' Loan officers tighten standards very sharply for a few quarters, but ease up only gradually: two or three years pass before standards are back to their initial level. Commercial loans at banks plummet immediately after the tightening of standards and continue to fall until lenders ease up. Output falls as well..." (p. 10). But, changes in credit standards are not a pure reaction to changes in macroeconomic phenomena. Lown and Morgan (2001, 2002) and Lown, Morgan and Rohatgi (2000) extend a standard macroeconomic vector autoregression (VAR) model to include the commercial bank loan market, in particular including the lending standards survey index as a proxy for loan availability. Their basic finding is that the macroeconomic variables are *not* successful in explaining variation in the lending standards index.[6] Lown and Morgan (2001) conclude: "Even with the most conservative ordering – standards last – we find that shocks to standards account for most of the variance decomposition in lending and a sizable share of the variance of the decomposition of output. Standards remain important even when the model is extended to include various proxies for commercial credit quality and demand (business failures and the loan rate) forward looking variables (forecasted GDP and interest rate spreads)" (p. 3).

The theory we present has two main elements. The first element concerns the essence of banking. Banks produce private information about potential lenders (see Gorton and Winton (2003) for a review of the literature). When competing with each other to lend, banks produce information about potential borrowers in an environment where they do not know how much information is being produced by rival bank lenders.[7] The basic idea that we develop concerns the strategic use of the winner's curse by one bank against rival banks over time. A bank can produce more information than its rivals and then select all the better borrowers, leaving unknowing rivals with adversely selected loan portfolios. The second element relates to the industrial organization of the banking industry. While ultimately an empirical matter, strategic interaction between banks seems natural because banking is highly concentrated. Entry into banking is restricted by governments. In developed economics 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)).

Combining these two elements leads to a model in which banks collude to set high loan rates (hence loan rates are sticky) and implicitly agree not to expend enormous amounts on information production. The problem for maintaining the implicit agreement is that each bank does not know how much information rival

[6] They also find that changes in bank lending standards matter much more for the volume of bank loans and aggregate output than do commercial loan rates, consistent with the finding that loan rates do not move as much as would be dictated by market rates.

[7] Broecker (1990) observed that the information asymmetry also affects the banks themselves and means that banks compete with each other in a special way. In Broecker's (1990) model, banks use noisy, independent, credit worthiness tests to assess the riskiness of potential borrowers. Because the tests are imperfect, banks may mistakenly grant credit to high-risk borrowers who they would otherwise reject. As the number of banks increases, the likelihood that an applicant will pass the test of at least one bank rises. Banks face an inherent winner's curse problem in this setting. In Broecker's model banks do not behave strategically.

banks are producing about borrowers. Information production intensity is private information. Deviation from the arrangement occurs if a bank produces more information than its rivals and then accepts only high quality borrowers at the agreed (collusive) loan rate. Rivals are left with an adversely selected pool of lower quality borrowers. Banks can observe public information about rivals, namely, the size of banks' loan portfolios (number of loans that were granted) and the portfolio outcomes (the number of loans that defaulted). This public information is the basis for banks' beliefs about whether rival banks are following the implicit collusive arrangement or deviating. As in Green and Porter (1984), intertemporal incentives to maintain the collusive arrangement requires periods of "punishment," which here correspond to credit crunches. In a credit crunch all banks increase their information production intensity, their "lending standards," and stop making loans to some borrowers which previously were extended credit. These swings in credit availability are caused by banks' changing beliefs about the viability of the collusive arrangement.

A bank makes two strategic decisions each period, a loan rate is chosen and a level of information production intensity is chosen. We show that as a result of there being two actions, banks must look at two sources of public information, namely number of loans and the default performance of the loans, in order to detect the possibility of cheating on the arrangement. This result is important for the empirical tests.

Testing the implications of the infinitely repeated game of bank lending is difficult. The collusive arrangement of the model is subtle since it is implicit. Banks never formally collude, and they need not be rivals with regard to every type of loan in all geographical areas. The model is abstract in the sense that exact equilibrium strategies can not be explicitly stated, and there are likely many equilibria. Moreover, banks' beliefs are not observable, nor is information production intensity or lending standards. A robust prediction of the model, however, is that the relative performance of *other* banks matters for the decisions of each bank with respect to its own credit allocation. For example, if a bank's loan losses have been rising relative to those of rival banks, all banks may decide to raise their lending standards by producing more information. This could occur because a bank believes that another bank is deviating, and that other bank realizes that its rivals believe it is cheating. Therefore, all banks engage in punishment by increasing their standards and cutting off credit to lower rated borrowers. In a perfectly competitive market the history of rivals' relative performance would not matter.

The empirical strategy then is to find a relevant history of relative bank performance that banks use to form their beliefs. We must so this for some set of banks that could be rivals with regard to some category of loans. The first set of empirical tests focuses on U.S. credit card lending because it is highly concentrated with an identifiable group of banks that make the bulk of the loans in this market, so the rival banks can be identified. Next, we look at whether our measures of bank beliefs have predictive value for bank stock returns.

The second set of tests concerns whether the credit cycles induced by changes in bank beliefs, as proxied for by the measure of relative bank performance histories has implications for the business cycles and for systematic risks. In a vector autoregression we test whether measures of relative bank performance can explain (in the sense of Granger-causality) the Senior Loan Officer Opinion Survey of Bank Lending Practices index of lending standards tightening in a large sample of U.S. banks over time. We add a variety of macroeconomic variables, as well, and show our belief proxy is an autonomous cause of macroeconomic dynamics. Finally, we ask whether the beliefs measure is a priced factor in a Fama-French type three or four factor model. We find all the evidence to be consistent with the theory.

Aside from the empirical literature on credit crunches mentioned above (in footnotes), the other related work is Rajan (1994). 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. However, as pointed out by Weinberg (1995), the data on the growth rate of total loans and loan charge-offs in the Unites States from 1950 to 1992 do not show the pattern of increases in the amount of lending being followed by increases in loan losses. We test Rajan's idea more formally in the empirical section here.

We proceed in Section 2 to describe the stage game for bank lending competition, and we study the existence of stage Nash equilibrium and the model implication for lending standards. The stage game is a prelude to considering the infinitely repeated game, the subject of Section 3. In Section 4, we carry out empirical tests based on the theoretical predictions. Section 5 concludes the paper.

2 The Lending Market Stage Game

In this section we set forth the model and analyze the lending market stage game.

Suppose (without loss of generality) 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.[8] 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 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 applicant type. The credit worthiness test results in determining the type of an applicant, but there is a per applicant cost, $c > 0$, for each loan applicant. 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 is its credit or lending standard.[9] If a bank switches from not using the credit worthiness test to using it, we say that the bank has raised its lending or credit standards.[10] 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. Also, results of the test are the private information

[8] 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 incorporae this. But it would obscure the cyclical effects that are purely due to bank competition.

[9] 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.

[10] "Lending standards" are here equated with increased information production. Sometimes a "lending standard" is thought of as a score that is produced by a model. The model here envisions something perhaps broader, incorporating a culture that expresses a view about the score and how it is to be combined with other information the bank may have. Since "lending standards" are unobservable, part of the joint hypothesis tested in the empirical section is the idea that our interprettion of "lending standard" is correct.

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 test.

- Assumption 1: $p_g X > 1$, $p_b X < 1$, and $\lambda p_b X + (1-\lambda) p_g X > 1; 0 \leq X \leq 1$.

This assumption means that there exists some interest rate 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. (The face value of the loan F is equivalent to the interest rate, and later on we refer to F as the "loan interest rate.") It is also possible for banks to make profit from lending to both types of applicants without discriminating between the types.

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 $N_{\alpha i} \leq N - n_i$ 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. In general, $F_{\alpha i}$ could vary among the untested applicants that get approved by bank i, i.e., different applicants in the same category of "no test" could possibly get offers of loans at different interest rates. Therefore, we interpret $F_{\alpha i}$ as a vector of interest rates charged to those approved non-tested applicants.

For those applicants that are tested by bank i, the bank will observe a number of good type applicants, $N_{gi} \leq n_i$, and will then decide to approve applications to $N_{\beta i} \leq N_{gi}$ of the applicants that passed the test, and offer the approved applicants a loan at interest rate $F_{\beta i}$ (which could in principle vary across those offered loans). Bank i can also decide to approve applications to $N_{\gamma i} \leq n_i - N_{gi}$ 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.

We assume 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 portfolios sizes and outcomes are publicly observable. Banks cannot communicate with each other.

The stage strategy of a bank is:

$$s_i = \{n_i, N_\alpha(n_i, N_{gi}), N_\beta(n_i, N_{gi}), N_{\gamma i}(n_i, N_{gi}), F_{\alpha i}(n_i, N_{gi}), F_{\beta i}(n_i, N_{gi}), F_{\gamma i}(n_i, N_{gi})\}, \tag{1}$$

where:

n_i	:	the number of applicants that bank i tests;
N_{gi}	:	the number of good applicants found 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.

Figure 1 shows the timing of moves in the one period game.

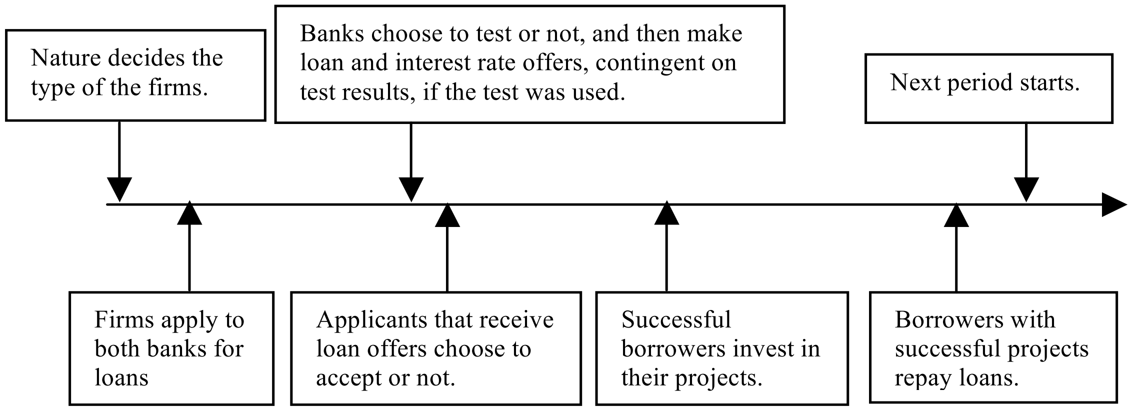

Figure 1: The Timing of the Stage Game

2.1 Stage Nash Equilibrium

We now turn to study the Nash equilibrium and the conditions for the existence of Nash equilibrium in the lending market stage game. We show a condition under which the only Nash equilibrium that exists is one in which neither bank conducts credit worthiness tests and both banks earn zero profits.

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

Proposition 1 *If* $c \geq \frac{(1-\lambda)\lambda(p_g-p_b)}{\lambda p_b+(1-\lambda)p_g}$*, then there exists a symmetric Nash equilibrium in which no bank conducts credit worthiness tests. If* $c < \frac{(1-\lambda)\lambda(p_g-p_b)}{\lambda p_b+(1-\lambda)p_g}$*, then there is no symmetric Nash equilibrium in which no bank conducts credit worthiness tests.*

The proof is in the Appendix.

Proposition 1 says that if the cost of testing each loan applicant is sufficiently high, i.e., $c \geq \frac{(1-\lambda)\lambda(p_g-p_b)}{\lambda p_b+(1-\lambda)p_g}$, then the there exists a Nash equilibrium in which no bank conducts credit worthiness tests and both banks earn zero profits.

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

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 test are conducted (as we will show in a moment). That is, credit worthiness testing is socially inefficient.

Now consider the case where both banks test all the applicants.

Proposition 2 *There is no symmetric Nash equilibrium in which both banks test all the applicants.*

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

Next we examine symmetric equilibria in which each bank tests a subset of the applicant pool.

If in equilibrium, each bank tests a subset of all applicants, the winner's curse effect may lead the banks to reject all those non-tested applicants. Assume the banks randomly pick $n < N$ applicants for testing, and offer loans to those that pass the test. To simplify the argument, assume that the interest rates offered to non-tested applicants is 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 that it is accepted by the applicant, the probability of this non-tested applicant being a bad type is:

$$\theta \doteq \Pr(\textit{bad type}|\textit{not tested}) = \frac{\frac{n}{N}\lambda + (1-\frac{n}{N})\frac{1}{2}\lambda}{\frac{n}{N}\lambda + (1-\frac{n}{N})\frac{1}{2}}.$$

When n is close to N, θ can be very close to 1. This has a sensible implication for lending standards. When banks conduct credit worthiness testing, lending standards (loosely defined) can rise in two ways. First, those applicants that were tested are 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, and this naturally creates a "credit crunch," in which a non-tested (by either bank) applicant does not get a loan even it is of good type.

The possibility of non-existence of a profitable interest rate for non-tested applicants will be discussed in the proof of the proposition below.

Proposition 3 *There does not exist a symmetric Nash equilibrium in which each bank test $0 < n < N$ applicants.*

The proof is in the Appendix. The basic argument similar to that of Proposition 2.[11]

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. However, in the repeated setting, banks can earn strictly positive profit and we can not rule out the credit worthiness testing on the equilibrium path. Indeed, the existence of the credit worthiness testing and the winner's curse effect makes the competition more complicated than the usual Bertrand competition without information acquisition.

It is straightforward to characterize the optimal payoffs that the two banks receive in the stage game.

Lemma 1 *Under Assumption 2, the maximum joint stage payoff for banks is reached without credit worthiness test.*

Proof. If a bank does not carry out a credit worthiness test on an individual applicant and charges F, then the expected payoff from a loan to that individual applicant is:

$$E\pi = \lambda p_b F + (1-\lambda)p_g F - 1,$$

which is maximized at $F = X$. The gain from credit worthiness testing is $\lambda(1 - p_b F)$, which is decreasing in F. Under Assumption 2, charging X to all loan applicants without testing is more profitable than charging X to only those applicants that pass the test. ■

Intuitively, a higher interest rate (higher F) will make the credit worthiness test less valuable. However, when the banks collude by offering a profitable interest rate to the applicants without testing, there are incentives for both banks to undercut the interest rate in order to get more applicants or to conduct credit

[11] Banks could play more general mixed strategies. For example, banks could mix between testing n_1 applicants and testing n_2 applicants. We do not delve into these strategies.

worthiness test in order to get better applicants. This two dimensional competition, through the loan interest rate and the amount of information acquisition results in some special features to the game, as we show in the next section.

3 Repeated Competition

Let F^* be the interest rate corresponding to zero profits in the loan market when there is no testing.[12] In the one period game with symmetric pure strategies, for any $F > F^*$, it is more profitable for banks to lend without conducting credit worthiness tests. Setting a (collusive) loan interest rate of $F = X$ would be the most profitable case for both banks, but this outcome cannot be achieved in one period. In repeated competition banks will try to collude to charge $F = X$ without using credit worthiness tests. But collusion can only be supported if there are intertemporal incentives, that is, if banks have a way to punish each other to prevent deviation. In deciding if there is a need for punishment, a bank can, at the end of each period, observe the number of loans made by a rival (the loan portfolio size) and the number of loans defaults that occurred. There are two ways to deviate. Lowering the loan interest rate attracts more applicants but this can be imperfectly detected by monitoring the loan portfolio size.[13] Alternatively, a bank can engage in more intensive information production, by testing, to improve loan quality. This can only be detected by monitoring the rival's loan portfolio default performance. A bank's use of testing cannot be perfectly monitored by rival banks since both good and bad type applicants have a risk of failure. So, observing the ex post loan performance does not provide full information about whether a bank deviated by conducting credit worthiness tests.

In general, banks can base their strategies on all available information, both public and private. Note that, given bank A's strategy, bank B's strategy will affect bank A's loan portfolio size and composition, i.e., the proportion of bad type applicants in the portfolio. If one bank's strategy only depends on public information, the other bank can not do better by making its strategy dependent on both public information and its private information. We therefore consider sequential equilibria in which banks' strategies will depend on public information. The class of sequential equilibria (see Kreps and Wilson (1982)) that depends only on public information is called "Perfect Public Equilibria" (PPE). See Fudenberg, Levine, and Maskin (1994). Banks can compete by changing their offered loan interest rates and by changing their credit standards, i.e., the amount of information that they produce. The available public information at the end of each period is the number of loans that the rival made and the number of those loans that defaulted.[14]

In this section we restrict attention to symmetric PPE (SPPE) (defined below). Aside from seeing how the repeated game works, the main point of this section is the demonstration that because banks have two actions that they can use to compete (i.e., change lending rates and increase information production), banks' beliefs must be based on the history of banks' portfolio size as well as banks' loan default performance.

[12] See Lemma 2 of the Appendix.

[13] If both banks make identical offers to a borrower, the borrower randomly chooses a bank. So, portfolio sizes may differ even if no bank is deviating.

[14] As we noted above, observing the ex post loan performance of a bank's porfolio cannot give full information about whether the bank deviated by conducting credit worthiness tests because both good and bad type borrowers have a risk of failure. In other words, the support of the distribution of outcomes is independent of the banks' actions, with regard to interest rate and lending standard. This also implies that Bayes' Rule can be used off the equilibrium path.

3.1 The Formal Model

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 interest rate on the loan offered to the applicants;

(iii) its 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 as in (1). 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:

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

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. 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. By definition:

$$\begin{aligned} D_{it} &= D_{\alpha it} + D_{\beta it} + D_{\gamma it} \\ \chi_{it} &= \chi_{\alpha it} + \chi_{\beta it} + \chi_{\gamma it}. \end{aligned}$$

At the beginning of period T bank i has an information set: $h_i^{T-1} = \{a_{it}, K_{it}, \kappa_t\}_{t=0}^{T-1} \in H_i^{T-1}$, where $a_{it} = \{n_{it}, N_{\alpha it}, N_{\beta it}, N_{\gamma it}, F_{\alpha it}, F_{\beta it}, F_{\gamma it}\}$ is the action of each bank (by convention $h_i^{-1} = \varnothing$). A (pure) strategy for bank i associates a schedule $\sigma_{iT}(h_i^{T-1})$ with each $T = 0, 1, ...$ and σ_{iT}: $H_i^{T-1} \to S$, where S is the stage strategy space with element s_{it}, defined earlier. Denote the public information as $h^{T-1} = \{\kappa_t\}_{t=0}^{T-1} \in H^{T-1}$, and a (pure) strategy for bank i associates a schedule $\sigma_{iT}(h^{T-1})$ with each $T = 0, 1, ...$ and σ_{iT}: $H^{T-1} \to S$.

Given λ, p_g, and p_b (i.e., nature's uncertainty), a strategy profile (σ_1, σ_2), with $\sigma_i = \{\sigma_{it}(.)\}_{t=0}^{\infty}$, $i = 1, 2$, recursively determines a stochastic process of credit standards ($\{n_{it}\}_{t=0}^{\infty}, i = 1, 2$), interest rates ($\{F_{it}\}_{t=0}^{\infty}, i = 1, 2$), bank portfolio sizes, and loan performances ($\{\kappa_{it}\}_{t=0}^{\infty}, i = 1, 2$). The expected pathwise payoff for bank i is:

$$v_i(\sigma_1, \sigma_2) = E \sum_{i=0}^{\infty} \delta^t \pi_i(s_{1t}, s_{2t}),$$

where

$$\pi_i(s_{1t}, s_{2t}) = (\chi_{\alpha it} F_{it} - D_{\alpha it}) + (\chi_{\beta it} F_{\beta it} - D_{\beta it}) + (\chi_{\gamma it} F_{it} - D_{\gamma it}) - n_{it} c.$$

In the next section we turn to determining the Perfect Public Equilibria of the repeated lending game.

3.2 Factorization of Perfect Public Equilibrium

A Perfect Public Equilibrium (PPE) is a profile of public strategies that, starting at any date t and given any public history h_i^{t-1}, forms a Nash equilibrium from that point on (see Fudenberg, Levine, and Maskin (1994)). As noted earlier, a bank cannot do better by playing a non-public strategy, if the other bank is using a public strategy (i.e., one based on public information). Private information about past actions, use of the credit worthiness tests or loan interest rates, do not affect behavior because such information is not public. We will show that a PPE induces a PPE in every continuation game.[15] We now turn to characterizing the PPEs.

Let $h_t = \kappa_t$ be the history of realized public information, namely the number of loans made (loan portfolio size) and the number of defaults (loan performance) for each bank at the end of each period t. Let $V \equiv \{v(\sigma) \mid \sigma \text{ is an } PPE\}$ be the set of PPE payoffs. Note that, by the existence of the stage game Nash equilibrium, V is not empty. To characterize the set of PPE payoffs we will follow Abreu, Pearce, and Stacchetti (APS) (1986, 1990). The basic idea of APS is that each stage of the repeated lending game can be represented as a static game with payoffs equal to the state game payoffs augmented by continuation payoffs, i.e., the present value of the future payoffs. The continuation payoffs depend on the current play of the stage game. Because the loan portfolio sizes and the number of defaults are publicly observed at the end of the period, the continuation strategy profile is induced by this public information (i.e., a PPE). Therefore, this profile is common knowledge, and is itself a PPE. The value of the continuation profile is therefore always in V. APS define the notion of "self-generation" to "factor" a PPE into the first period payoff and the continuation payoff, depending on the first period outcome. The key to finding the subgame perfect sequential equilibrium is the construction of self-generating sets. Intuitively, a set W contained in $\mathcal{R}^N$ is "self-generating" if each value in W can be supported by continuation values which themselves have values in W. The concept of self-generation is formalized by the construction of an operator or map $T(V)$. Suppose that V is the set of all possible payoffs tomorrow. Let T denote the set of payoffs today using pure strategies and consistent with Nash play in the game for some u in V. Define the operator $T(V)$ which yields the set of PPE values, V^*, as the largest invariant, or "self-generating" set. For any V containing $(0, 0)$ (the stage Nash payoffs), which is the expected payoff from stage Nash equilibrium, the operator is defined as follows:

$$\begin{aligned} T(V) \quad &\equiv \quad \{(v_1, v_2) : \exists (s_1, s_2) \in S \times S \text{ and } (u_1, u_2) \text{ with } u_i : \mathcal{N}^4 \to co(V) \\ \text{such that} \quad &: \quad v_i = E[\pi_i(s_1, s_2) + \delta u_i(\kappa_t)] \text{ for } i = 1, 2 \\ \text{and} \quad &: \quad v_i \geq E[\pi_i(s_i', s_{-i}) + \delta u_i(\kappa_t')] \text{ for any } s_i' \in S \text{ and } i = 1, 2. \end{aligned}$$

This operator factors the supergame into two components: current-period strategies $(s_1, s_2) \in S \times S$ and the continuation value (u_1, u_2) drawn from the convex hull of the set V.[16]

Lemma 2 *The operator T maps compact sets to compact sets.*

[15] A PPE toegether with any beliefs consistent with Bayes' rule consitutes a Perfect Bayesian Equilibrium (PBE), but a PBE need not be a PPE. See Fudenberg, Levine, and Maskin (1994) for an example.

[16] By using the convex hull of V, we are allowing public randomization. Implicitly, we assume that in each period, there is a lottery that determines which Nash equilibrium will be played next period, as a function of the actions chosen by the banks this period. The randomization (i.e., the lottery) is public, so this is like having a "sunspot" determine the continuation values. This convexifies the set of equilibrium continuation values. This is a standard assumption. E.g., see Cronshaw and Luenberger (1994).

Proof. This follows because the constraints entail weak inequalities, the feasible set is compact, and the utility and constraint functions are real-valued, continuous and bounded. ■

This property of T is crucial for applying the methodology of Abreu, Pearce, and Stacchetti (1986, 1990). In particular, let V_0 be compact and contain all feasible, individually rational payoffs (for example, $V_0 = [0, \frac{1}{\delta}N[\lambda p_b X + (1-\lambda)p_g X - 1]] \times [0, \frac{1}{\delta}N[\lambda p_b X + (1-\lambda)p_g X - 1]])$, and define $V_{n+1} = T(V_n)$, $n \geq 0$. Then the definition of T implies that $T(V_n) \subseteq V_n$. Using this and the fact that V_n is nonempty for each n (since repeating stage Nash payoff is always in every V_n), $V^* = \lim_{n\to\infty} V_n$ is a nonempty, compact set. Following the arguments in Abreu, Pearce, and Stacchetti (1990), V^* is the largest invariant set of T, and thus is equal to the set of public perfect equilibrium values of this game.

3.3 Symmetric Perfect Public Equilibrium

We now examine symmetric PPE (SPPE) in which asymmetric play is allowed after the first period stage game is played symmetrically.[17] We focus on demonstrating that the banks' continuation play depends on the history of the number of loans made by each bank and on the number of loan defaults in each bank's portfolio. These results then motivate the empirical analysis.

Any symmetric perfect public equilibrium σ can, as discussed, be *factored* into a first-period strategy s and a *continuation payoff function* $u : \mathcal{N}_+^4 \to V^*$. An SPPE is defined as follows:

Definition: *A Symmetric Perfect Public Equilibrium (SPPE) is a Perfect Public Equilibrium that can be decomposed into the first period stage strategies and continuation value functions* (s_1, s_2, u_1, u_2) *such that:*

$$s_1 = s_2 \text{ and } u_1(D_1, D_2, \chi_1, \chi_2) = u_2(D_2, D_1, \chi_2, \chi_1).$$

According to the definition, the stage game strategies are the same, but the continuation strategies can differ though they must have the same continuation value. 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.

We will show that if there is no credit worthiness testing (because, by assumption, the cost is too high), then the continuation values will only depend on the loan portfolio sizes of the two banks. At a profitable interest rate, when Bank 1 gets more loans than its rival, the continuation value of Bank 1 should be lower, to eliminate the incentive of the banks to deviate by undercutting interest rates to get more loans. However, when there is credit worthiness testing, it may not be true that making more loans is always better. A bank can deviate by testing, "raising credit standards," resulting in the other bank lending to bad type applicants rejected by the first bank. This is the strategic use of the winner's curse by one bank against its rival. Due to that possibility, we will show that loan performance (number of defaults in each bank portfolio) will also affect the continuation value.

Proposition 4 *In any SPPE with* $s = (n = 0,\ N_\alpha,\ F_\alpha)$ *played symmetrically on the equilibrium path, where* F_α *is a constant larger than* $F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g}$ *and* $N_\alpha = N$*, if* $c < \lambda(1-\lambda)(p_g - p_b)F_\alpha$*, then the continuation value functions cannot only depend on* (D_1, D_2) *(i.e., only on the number of loans made by each bank).*

[17] We can prove that there does not exist any symmetric PPE in a strict sense (i.e., both banks behave the same way in the stage game and in the continuation game) other than the one in which the stage Nash equilibrium is played every period. The proof is available on request.

The proof is in the Appendix. The proof involves finding a deviating strategy such that the expected continuation payoffs are the same for both banks while there is a stage gain by conducting a credit worthiness test. The proposition says that banks' loan performances (i.e., number of defaults) matters in an SPPE with banks charging the same interest rate to all the applicants, and when they do not carry out credit worthiness testing. With the possibility of credit worthiness testing, variation in loan portfolio sizes is not enough to detect deviation through credit worthiness testing. When both banks offer loans to only a subset of the applicants without using the test, we have the following results.

Corollary 1 *In any SPPE with $s = (n = 0,\ N_\alpha,\ F_\alpha)$ played symmetrically on the equilibrium path, where F_α is a constant larger than $F^* = \frac{1}{\lambda p_b + (1-\lambda) p_g}$ and $2 \leq N_\alpha < N$, if $c < \lambda(1-\lambda)(p_g - p_b)F_\alpha$, then the continuation value functions cannot depend on (D_1, D_2) only (i.e., only on the number of loans made by each bank).*

The proof is in the Appendix.

Corollary 2 *In any SPPE with $s = (n = 0,\ N_\alpha,\ F_\alpha)$ played symmetrically on the equilibrium path, where $F_\alpha > F^*$ is a vector of different interest rates offered to the approved applicants and $N_\alpha \leq N$, if $c < \frac{2N-1}{2N}\lambda(1-\lambda)(p_g - p_b)\min\{F_\alpha\}$, then the continuation value functions cannot depend on (D_1, D_2) only (i.e., only on the number of loans made by each bank).*

The proof is in the Appendix.

The conclusion is that when the banks want to avoid the costly credit worthiness test on the equilibrium path, then it is not possible for the two banks to collude at a high loan interest rate in a PPE without looking at each other's loan performances. The possibility of deviating by using credit worthiness testing, and the resulting winner's curse effect, makes both banks strategies sensitive to each others' past loan performances, even though there is an *i.i.d.* distribution of borrower types.

Banks' strategies depend on the history of banks' loan portfolio performance and size. To help understand this issue for later empirical tests consider a simple example, with $N = 2$ applicants. Suppose Bank 1 deviates from the strategy $s = (n = 0, N_\alpha = 2, F_\alpha)$, by deviating to s' as follows: test one applicant; if it 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 loan is:

$$q_1 = \lambda(1 - p_b) + (1 - \lambda)(1 - p_g).$$

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

$$q_1' = \lambda(1 - p_b) + (1 - \lambda)[\lambda(1 - p_b) + (1 - \lambda)(1 - p_g)].$$

The likelihood of default is higher:

$$\Delta q_1 = q_1' - q_1 = \lambda(1 - \lambda)(p_g - p_b).$$

To detect a deviation, however, banks should compare their results. That is, they should check their loan performance difference. Looking at that difference, the results are different. 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:

$$q_2 = \lambda(1 - p_b)[\lambda p_b + (1 - \lambda)p_g] + (1 - \lambda)(1 - p_g)[\lambda p_b + (1 - \lambda)p_g] < q_1.$$

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

$$q_2' = \lambda(1 - p_b)[\lambda p_b + (1 - \lambda)p_g] + (1 - \lambda)[\lambda(1 - p_b) + (1 - \lambda)(1 - p_g)]p_g.$$

And:

$$\Delta q_2 = q_2' - q_2 = \lambda(1 - \lambda)(p_g - p_b) = \Delta q_1.$$

The measure of "performance difference" detects the deviation effectively because it excludes the case where both banks perform poorly. Excluding this case is empirically important because this case can result from aggregate shocks, which we do not model.

In the Appendix, we construct a detailed example, using a Green-Porter (1984) type trigger strategy, in which banks change their lending standards based on the history of their performance differences.

In the next section, we carry out different empirical tests based on "performance difference" measures, and as we have discussed, we expect that a large "performance difference" will cause a "punishment" in the form of a credit crunch induced by the switch to using the costly credit worthiness tests.

4 Empirical Tests

The model is abstract in the sense that exact equilibrium strategies can not be explicitly stated, and there are likely many equilibria. It is not immediately obvious how to test such a model. In addition, formulating empirical tests of the repeated lending market game requires confronting a number of other large problems. First, important variables are unobservable, such as lending standards and bank beliefs. Second, rival banks must be identified and it is not clear how to do this. Banks may compete based on geography or product line, or both. In this section we explain how we confront these issues. We will then present a variety of evidence. We also will examine some alternative explanations for why this variable might matter, for example, learning about the macroeconomy. Overall we find broad support for the repeated credit cycle model.

Lending standards are unobservable, so empirical tests cannot be based directly on standards. In the repeated game the decision to increase information production or raise standards results from a change in beliefs about rival banks' actions. But banks' beliefs are also not observable. However, we have shown that equilibria depend on the history of public information; beliefs and changes in beliefs are based on public information. Therefore, 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, past histories of rival banks should affect the decisions of any given bank. The basic empirical strategy is to construct measures of the relative performance histories of banks. We construct indices of the absolute value of the difference in loan loss ratios and test whether the history of such a variable has predictive power for future lending decisions, loan losses, and bank stock returns.[18] If banks' beliefs about rivals' actions changed based on this parameterization of the public history, then when this measure increases, i.e., there is a greater dispersion of relative performance, then banks reduce their

[18] Note that the absolute value is important because even if a bank is doing relatively better than its rivals it knows that the rivals believe that it has deviated and so rivals will raise their information production, causing the better performing bank to also raise its information production. Banks punish simultaneously resulting in the credit crunch.

lending and increase its quality, resulting in lower loss ratios in the future. The test focuses on the general notion of imperfect competition in bank lending, rather than the specific set of equilibria in which banks punish each other by increasing information production, rather than increasing interest rates.

The second challenge in testing concerns identifying rival banks. To test the theory, we must identify banks that are, in fact, rivals in a lending market. It is not clear whether banks compete with each other in all lending activities or only in some specialized lending areas. It is also not clear whether bank competition is function of geography or possibly bank size. In the U.S., for example, banks can compete for loans anywhere in the world, regardless of their location. It is often stated that banks tend to specialize in lending to specific sectors (e.g., the steel industry or hospitals), in certain geographical areas (the Southwestern U.S. or Latin America), or to certain types of applicants (e.g., consumers who want home mortgages, small businesses, or large corporations). But, the data are not fine enough to assess this specialization notion. It is not clear whether the theory applies to all lending or to narrow categories. Banks could collude on some products, in some geographical areas, but not on other products or in other areas. This is an empirical issue, so we will examine both possibilities.

Broadly, the empirical analysis is in two parts. First, we examine a narrow category of loans, credit card lending, where there are a small number of banks that appear to dominate a market. We base the parametrization of bank's relative histories (which we hypothesize is the basis of their belief formation)on this narrow category of lending. Since it is not clear which banks are rivals, we first analyze this lending market by examining banks pairwise. Unfortunately, the Federal Reserve Call Reportsonly have the specific credit card data for a short period of time, an econometric issue we address below. We also ask whether the our parameterization of banks' relevant histories has any predictive power with respect to future bank stock returns.

Secondly, we turn to a broader examination of the theory in several parts. (1) We form the index of relative bank performance differences based on all commercial and industrial loans. If beliefs are, in fact, based on this information, then we should be able to explain (in the sense of Granger causality) the time series of lending standard survey responses (the percentage of banks reporting "tightening" their standards) that Lown and Morgan (2001) and Schreft and Owens (1991) analyzed. (2) We examine the explanatory power of the performance difference index with respect to business cycle dynamics. We show that the performance difference index Granger-causes all the macroeconomic variables, but is not in turn caused by any of the macroeconomic variables. That is, banks cause macroeconomic fluctuations to a significant degree. (3) If credit crunches are endogenous, and a systematic risk, then they should be a priced factor in an asset pricing model of bank stock returns. Therefore, our final test is to ask whether the parameterization of banks' relevant histories is a priced factor in a three or four factor Fama-French asset pricing setting. We find that it is.

4.1 The Credit Card Loan Market

In the U.S. credit card lending market rival banks are identifiable because credit card lending is highly concentrated and this concentration has been persistent. The Federal Reserve has collected data on credit card lending and related charge-offs since the first quarter of 1991 in the Call Reports. The data we use is at the bank holding company level, as aggregated by the Federal Reserve Bank of Chicago. Thus, we are thinking of banks competing at the holding company level rather than at the individual bank level. For each bank holding company, we collect quarterly data from 1991.I through 2000.IV for "Credit Cards and

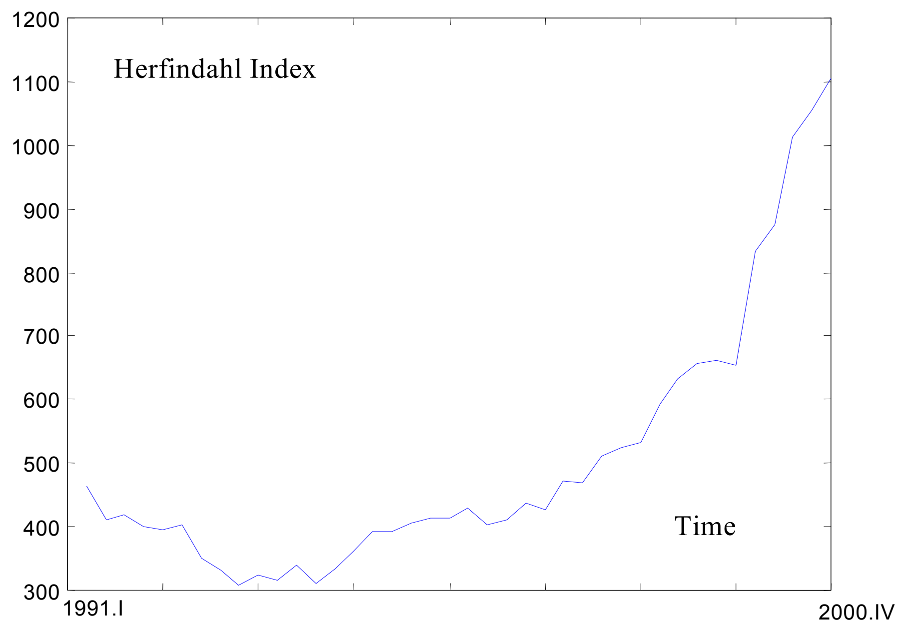

Figure 2: Herfindahl Index

Related Plans," as well as some other variables discussed below.[19]

The high concentrated is shown by the Herfindahl Index for credit card loan market pictured in Figure 2.[20]

Figure 3 shows the proportion of credit card loans for the top 10, 30, and 50 bank holding companies.

We can see from Figures 2 and 3 that over time the credit card loan market has become increasingly concentrated, and the market shares of the top bank holding companies have become increasingly larger.[21]

4.1.1 Data Description

The basic idea of the first set of tests is to regress an individual bank's credit card loans outstanding, normalized by total loans or total assets, or the bank's (normalized) credit card loss rate, on lagged variables that we hypothesize predict the bank's decision to make more credit card loans or to reduce losses on credit card loans (by making fewer loans or more high quality loans). Macroeconomic variables that characterize the state of the business cycle are one set of predictors. Lagged measures of the bank's own performance in the credit card market are another set of predictors. The key variables concern measures of bank's histories

[19] The data are not reported more frequently than quarterly.

[20] A Herfindahl Index is constructed as $\sum_i (\frac{firm\ i\ credit\ card\ loan\ size}{total\ credit\ card\ loan\ size} \times 100)^2$.

[21] Ausubel (1991) observed that "the bank credit card market ... casually appears to be a hospitable environment for the model of perfect competition. Nevertheless, ... credit card interest rates have been exceptionally sticky relative to the cost of funds. Moreover, major credit card issuers have persistently earned from three to five times the ordinary rate of return in banking" (p. 50). Ausubel (1991) proposed an explanation for these phenomena, essentially arguing that the credit card market is not perfectly competitive because of consumer behavior. We offer a nonmutually exclusive viewpoint, namely, that the stickiness of credit card interest rates indicates that credit card issuers are competing through non-price strategies instead of competing in price, to drive it down towards marginal cost.

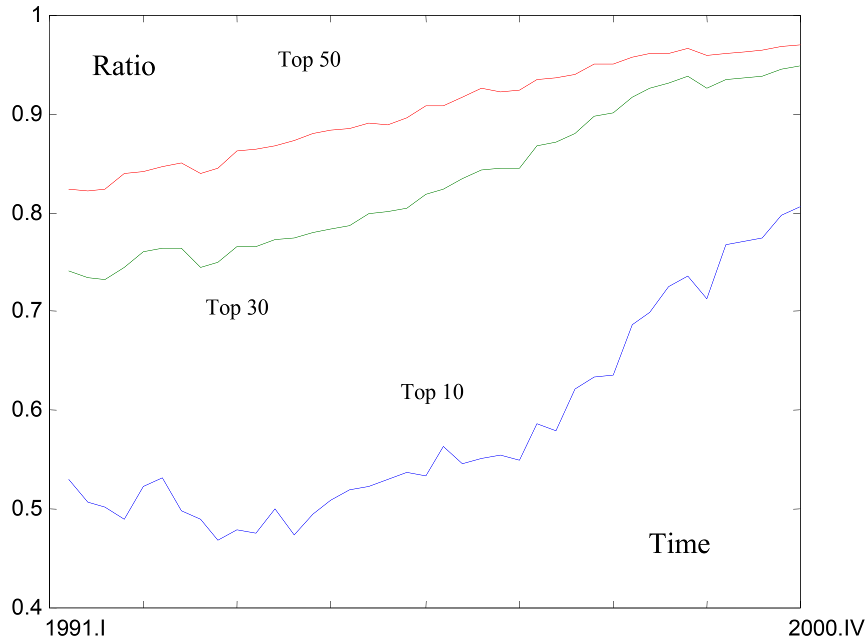

Figure 3: Shares of Top Bank Holding Companies in Credit Card Loan Market

that we hypothesize are the basis for banks' beliefs that rivals have deviated. Our main hypothesis is that these measures of bank histories will be significant, even conditional on all the other variables.

The tests require two types of data: data on individual banks and macroeconomic data. In addition to collecting the quarterly data bank holding company from 1991.I to 2000.IV for "Credit Cards and Related Plans(CLS)," we also use "Charge-offs on Loans to Individuals for Household, Family, and Other Personal Expenditure – Credit Cards and Related Plans (CCO)," "Recoveries on Loans to Individuals for Household, Family, and Other Personal Expenditures – Credit Cards and Related Plans (CRV)," "Total Loans and Leases, Net (TLS)," and "Total Assets ($ASSET$)."

We construct the following variables:

$$\begin{aligned} \text{Credit Card Loan Loss Rate } (CLL) &= \frac{CCO - CRV}{CLS}, \\ \text{Credit Card Loans on Total Loans Ratio } (CRL) &= \frac{CLS}{TLS}, \\ \text{Credit Card Loans on Total Assets Ratio } (CRA) &= \frac{CLS}{ASSET}. \end{aligned}$$

Each variable is constructed for each bank holding company for each quarter, with the exception of the Aggregate Credit Card Loan Loss Rate, which measures the state of the banking industry with respect to credit card loan losses.

With respect to macroeconomic data we use quarterly macroeconomic data from the Federal Reserve Bank of St. Louis for the period 1991.I to 2000.IV: "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)."[22]

4.1.2 Pairwise Tests on Rival Banks

We want to empirically test whether the history of the credit card loan performance of a bank affects other banks' credit card lending decisions. We will do this in several ways. First, we look at banks pairwise. We do this because we have only 40 periods of quarterly observations for each bank. We select 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 2000.IV. These six banks are:

- CITICORP, NEW YORK, NY (CITI);
- BANK ONE CORP, CHICAGO, IL (BONE);
- MBNA CORP, WILMINGTON, DE (MBNA);
- BANK OF AMER CORP, CHARLOTTE, NC (BOAM);
- CHASE MANHATTAN CORP, NEW YORK, NY (CHAS);
- WACHOVIA CORP, WINSTON-SALEM, NC (WACH).

We ask whether bank holding company i's credit card loan loss rate and the proportion of credit card loans on total loans or on total assets are affected by the other bank holding companies' past loan performance, given bank holding company its own past loan performance. In general, we run the following regression for each bank holding company i:

$$y_{it} = \alpha_{ij} x_t + \beta_{ij} w_{it} + \sum_{j \neq i} \gamma_{ij} z_{ijt} + \varepsilon_{it},$$

where

$$\begin{aligned} y_{it} &= CLL_{it},\ CRL_{it},\ \text{or } CRA_{it}, \\ x_t &= (C, T, S_1, S_2, S_3, DPI_t, FFR_t, UMP_t), \\ w_{it} &= (CLL_{it-1}, CLL_{it-2}, CLL_{it-3}, CLL_{it-4}), \\ z_{ijt} &= (\left|\Delta CLL_{ijt-1}\right|, \left|\Delta CLL_{ijt-2}\right|, \left|\Delta CLL_{ijt-3}\right|, \left|\Delta CLL_{ijt-4}\right|), \end{aligned}$$

and α_{ij}, β_{ij}, and γ_{ij} are the coefficients for x, w, and z, respectively. C is the constant term, T is the time trend, S_1 is the seasonal dummy for first quarter, S_2 is the seasonal dummy for second quarter, and S_3 is the seasonal dummy for third quarter. We do not include lags of DPI_t, FFR_t, or UMP_t because the main results are not affected by adding them. Since some bank holding companies might have systematically higher (or lower) loan loss rates than another bank holding companies, we first take out the mean from each CLL_i, and then take the difference to get ΔCLL_{ji}. In this way, $|\Delta CLL_{ji}|$ reflects the relative performance of the two banks.

$|\Delta CLL_{ji}|$ is the key variable. The idea of the test is to condition on the state of the macroeconomy and bank holding company i's own past performance, and then ask whether bank holding company i's

[22] We collected the monthly data for the Unemployment Rate (UMP), Disposable Income (DPI), Federal Funds Rate (FFR), and calculated the three-month averages to get the quarterly data. Moreoever, DPI is normalized by GDP.

CLL	$CITI$	$BONE$	$MBNA$	$BOAM$	$CHAS$	$WACH$
$CITI$	—	−0.1896 (0.1038) *	−0.3115 (0.0677) *	0.1160 (0.7261) –	−0.0597 (0.9829) –	−0.2686 (0.0013) **
$BONE$	−0.3339 (0.0010) ***	—	−0.4543 (0.0002) ***	−0.3385 (0.2393) –	−0.4876 (0.0656) *	−0.2546 (0.1993) –
$MBNA$	−0.0025 (0.9101) –	−0.0114 (0.8002) –	—	0.0089 (0.6759) –	0.0790 (0.0865) #	−0.0724 (0.3747) –
$BOAM$	−0.1310 (0.9289) –	−0.1666 (0.3809) –	−0.3834 (0.0002) ***	—	0.4371 (0.0002) ###	−0.4024 (0.4510) –
$CHAS$	−0.1328 (0.7765) –	−0.0170 (0.8690) –	0.0603 (0.4808) –	0.0784 (0.2212) –	—	−0.1906 (0.5896) –
$WACH$	−0.1278 (0.0000) ***	−0.0809 (0.3120) –	−0.2117 (0.0063) ***	0.0236 (0.9471) –	−0.0198 (0.0181) **	—

Table 1: Results with CLL as the dependant variable

lending decisions depend on observed differences between it's own past performance and that of its rival, bank holding company j. In the theory, banks form beliefs based on public information about rivals and about themselves. That is, bank holding company i's beliefs about whether rival bank holding company j is deviating is hypothesized to be a function of some measure of the relative performance of its own credit card loans and the performance of its rival. It is not clear how to parameterize measures of the differences in relative performance that might be the basis for forming those beliefs. We use the absolute difference of the loan losses of two the bank holding companies, i and j. The idea is that when banks observe too large a relative difference in loan performance they might attribute the difference to one bank having deviated, and as a result they simultaneously raise their lending standards.

For each measure of the relative difference in loan performance, we test whether $\gamma = 0$. As discussed above, we examine regressions pairwise for each pair of bank holding companies. Therefore, we run the following pairwise regression for each bank holding company i and bank holding company $j \neq i$:

$$y_{it} = \alpha_{ij} x_t + \beta_{ij} w_{it} + \gamma_{ij} z_{ijt} + \varepsilon_{it}, \text{ for } j \neq i. \tag{2}$$

We use the Wald test (chi-squared distribution) to test $\gamma = 0$. The results are shown in Tables 1-3.[23]

Tables 1-3 present the results for the pairwise regressions while

$$z_{ijt} = \left(\left| \Delta CLL_{ijt-1} \right|, \left| \Delta CLL_{ijt-2} \right|, \left| \Delta CLL_{ijt-3} \right|, \left| \Delta CLL_{ijt-4} \right| \right).$$

We report the average value of the coefficients of z_{ij}, and the p-value (in parenthesis) of the Wald test ($\chi^2(4)$). Significant negative coefficients are marked by '$*$,' and significant positive coefficients are marked

[23] The result in entry (i, j) in the table comes from the regreesion with bank i's loan loss (or asset allocation) being the dependent variable.

CRL	$CITI$	$BONE$	$MBNA$	$BOAM$	$CHAS$	$WACH$
$CITI$	—	−0.4807 (0.004) ***	0.1403 (0.6713) –	−0.2671 (0.0926) *	1.2131 (0.0869) #	−0.5353 (0.0004) ***
$BONE$	−1.2008 (0.0003) ***	—	−2.4739 (0.0000) ***	−1.6719 (0.0609) *	−1.4095 (0.5178) –	−1.9717 (0.0294) **
$MBNA$	0.2569 (0.8386) –	0.8216 (0.0491) ##	—	−0.6914 (0.3577) –	−0.5540 (0.4128) –	1.1749 (0.0004) ###
$BOAM$	−0.2932 (0.0002) ***	−0.2859 (0.0274) **	−0.2608 (0.2543) –	—	0.2274 (0.0125) ##	−0.2283 (0.5495) –
$CHAS$	−0.2586 (0.9027) –	−0.1209 (0.2272) –	−0.1075 (0.9810) –	−0.1433 (0.6790) –	—	−0.4296 (−0.0771) *
$WACH$	−0.3865 (0.0095) ***	−0.8394 (0.0001) ***	−0.6496 (0.0059) ***	0.0345 (0.8199) –	0.7314 (0.0906) #	—

Table 2: Results with CRL as the dependant variable

CRA	$CITI$	$BONE$	$MBNA$	$BOAM$	$CHAS$	$WACH$
$CITI$	—	−0.2085 (0.0710) *	0.1959 (0.3413) –	−0.1331 (0.4040) –	0.7186 (0.0405) ##	−0.2197 (0.0582) *
$BONE$	−0.9125 (0.0002) ***	—	−1.8853 (0.0000) ***	−1.2954 (0.0486) **	−1.0538 (0.5572) –	−1.4485 (0.0392) **
$MBNA$	−0.6157 (0.9109) –	2.3238 (0.0285) ##	—	−0.8193 (0.8978) –	−2.7239 (0.0006) ***	3.0559 (0.0005) ###
$BOAM$	−0.2050 (0.0045) ***	−0.2311 (0.0279) **	−0.2309 (0.1486) –	—	0.1708 (0.0391) ###	−0.2361 (0.4878) –
$CHAS$	−0.1838 (0.8661) –	−0.1130 (0.2672) –	0.0859 (0.9456) –	−0.0090 (0.6709) –	—	−0.2390 (0.1080) *
$WACH$	−0.2504 (0.0215) **	−0.5720 (0.0003) ***	−0.4152 (0.0293) **	0.0418 (0.6935) –	0.4957 (0.0888) #	—

Table 3: Results with CRA as the dependant variable

by '#.' Broadly, the results are in line with the theory: most coefficients are negative, which matches the theory 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, we can observe a systematic pattern of competition between Citicorp, Bank One, and Wachovia; the credit card loan loss and credit card loan size (relative to total loans or total assets) for these banks significantly depend on the relative performance of each other.

The above results have the obvious problem that we do not know how many significant chi-squared statistics would be expected to be significant in a small sample. We can answer this issue using a bootstrap (see Horowitz (2001) for a survey). We use the bootstrap method to test if the results in Tables 1-3 can verify our conjecture that the measures of bank holding companies' loan performance affect each other's loan decisions. The Null hypothesis is that a bank holding company's loan decision only depends on the aggregate economic variables and its own past loan performance, i.e.:

$$H_0 : y_{it} = \alpha_i x_t + \beta_i w_{it} + u_{it}.$$

The alternative hypothesis comes from the pairwise regression for each bank holding company i and bank holding company $j \neq i$:

$$H_1 : y_{it} = \alpha_{ij} x_{it} + \beta_{ij} w_{it} + \gamma_{ij} z_{ijt} + \varepsilon_{it}, \text{ with } \gamma_{ij} < 0.$$

In order to test the Null hypothesis, we use the bootstrap to obtain an approximation to the distribution of a Significance Index, SI, defined below, and then find the p-value of $S\dot{I}^*$ (the Significance Index from the pairwise regressions using the original data). For each round of the bootstrap, the Significance Index is constructed as follows. For each of the 30 pairwise regressions, when the average coefficient of z_{ijt} is negative, if the chi–squared-statistic is significant at the 99% confidence level, add a value of 4 to SI, if it is significant at the 95% confidence level , add a value of 3 to SI, if it is only significant at the 90% confidence level, add a value of 2 to SI, and add a value of 1 otherwise; when the average coefficient of z_{ijt} is negative, if the chi–squared-statistic is significant at the 99% confidence level, add a value of -4 to SI, if it is significant at the 95% confidence level , add a value of -3 to SI, if it is only significant at the 90% confidence level, add a value of -2 to SI, and add a value of -1 otherwise. The index SI takes care of both the significance and the sign of the coefficients of z_{ijt}. If the p-value of SI^* is small enough, we can reject the Null hypothesis.

The bootstrap algorithm is as follows:

Step 1: Run the OLS regression $y_{it} = \alpha_i x_t + \beta_i w_{it} + u_{it}$, for the three cases where $y_{it} = CLL_{it}$, CRL_{it}, or CRA_{it}, and use the estimated coefficients, $\widehat{\alpha}_{OLS}$ and $\widehat{\beta}_{OLS}$, to generate the residuals u^*_{it}.

Step 2: By hypothesis, the residuals u^*_{it} are i.i.d. so we can sample from u^*_{CLLit} to generate new CLL^*_{it} using $CLL^*_{it} = \widehat{\alpha}_{CLLi} x_t + \widehat{\beta}_{CLLi} w_{it} + u^*_{CLLit}$. This creates new w^*_{it} and z^*_{ijt}, which are necessary since z_{ijt} and some of the w_{it} variables are lags of CLL_i and CLL_j.

Step 3: Use u^*_{it} , for $y_{it} = CRL_{it}$ and CRA_{it}, to generate new CRL^*_{it} and CRA^*_{it} using $CRL^*_{it} = \widehat{\alpha}_{CRLi} x_t + \widehat{\beta}_{CRLi} w^*_{it} + u^*_{CRLit}$ and $CRA^*_{it} = \widehat{\alpha}_{CRAi} x_t + \widehat{\beta}_{CRAi} w^*_{it} + u^*_{CRAit}$.

Step 4: Use y^*_{it}, x^*_{it}, w^*_{it}, and z^*_{jit} to run the pairwise regression $y^*_{it} = \alpha x^*_{it} + \beta w^*_{it} + \gamma z^*_{jit} + \varepsilon^*_{it}$, and calculate the Significant Index SI.

Step 5: Repeat Step 2 to Step 4 $10,000$ times, and obtain the distribution of SI.

Step 6: Calculate the p-value of SI^*, i.e. $\Pr(SI \geq SI^*)$.

	p-value
SI_{CLL}	0.0197
SI_{CRL}	0.0005
SI_{CRA}	0.0049

Table 4: Boothstrap results

CLL	$CITI$	$BONE$	$MBNA$	$BOAM$	$CHAS$	$WACH$
$CITI$	—	−0.1845 (0.0082) ***	−0.7195 (0.0006) ***	−0.0017 (0.8264) −	−0.3415 (0.6929) −	−0.2451 (0.0217) **
$BONE$	−0.3434 (0.0001) ***	—	−0.3695 (0.0054) ***	−0.2316 (0.8644) −	−0.3215 (0.3174) −	−0.5564 (0.0001) ***
$MBNA$	−0.1317 (0.2469) −	−0.0343 (0.9268) −	—	−0.0830 (0.0937) *	0.0261 (0.0821) #	−0.0377 (0.4500) −
$BOAM$	−0.1439 (0.9580) −	−0.1836 (0.6709) −	−0.4283 (0.1388) −	—	0.4137 (0.0011) ###	−0.3658 (0.5556) −
$CHAS$	−0.0421 (0.9484) −	0.0053 (0.7126) −	−0.0279 (0.3056) −	0.1109 (0.2944) −	—	−0.1354 (0.8480) −
$WACH$	−0.1140 (0.0107) **	−0.1798 (0.0569) *	−0.0745 (0.0693) *	−0.0995 (0.7680)	0.0395 (0.0591) *	—

Table 5: Robustness check results with CLL as the dependant variable

The results are reported below. The critical values for the chi-squared distribution are: $\chi^2(4)_{0.90} = 7.78$, $\chi^2(4)_{0.95} = 9.49$, and $\chi^2(4)_{0.99} = 13.28$. The sample Significance Indices are: $SI^*_{CLL} = 34$, $SI^*_{CRL} = 36$, and $SI^*_{CRA} = 31$. The p-values are presented in Table 4.

We conclude that the Null hypothesis is rejected.

Could the above results be explained by some sort of learning? That is, 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 $|\Delta CLL_{ji}|$ 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 CLL_j in the regression of Bank i. Therefore, in the regression equation (2), we replace w_{it} with w_{ijt}:

$$w_{ijt} = (CLL_{it-1}, CLL_{it-2}, CLL_{it-3}, CLL_{it-4}, CLL_{jt-1}, CLL_{jt-2}, CLL_{jt-3}, CLL_{jt-4}). \tag{3}$$

We report the results in Tables 5-7.

Tables 5-7 present the results for the pairwise regressions with w_{ij} being replaced by w_{ijt} as in (3). We report the average value of the coefficients of z_{ij}, and the p-value (in parenthesis) of the Wald test ($\chi^2(4)$).

CRL	$CITI$	$BONE$	$MBNA$	$BOAM$	$CHAS$	$WACH$
$CITI$	—	−0.5019 (0.0098) ***	−1.1219 (0.1178) −	−0.4031 (0.4119) −	0.8807 (0.4979) −	−0.5358 (0.0000) ***
$BONE$	−1.4049 (0.0001) ***	—	−2.5697 (0.0002) ***	−1.1523 (0.2303) −	−1.8735 (0.3274) −	−2.7473 (0.0016) ***
$MBNA$	1.8208 (0.0094) ###	0.9289 (0.0395) ##	—	0.2279 (0.8813) −	−0.9744 (0.7303) −	1.3884 (0.0009) ###
$BOAM$	−0.4337 (0.0000) ***	−0.2148 (0.2866) −	−0.2740 (0.5081) −	—	0.2513 (0.0000) ###	−0.2541 (0.4786) −
$CHAS$	0.3313 (0.9088) −	−0.1541 (0.9753) −	−0.2404 (0.3684) −	0.2086 (0.5477) −	—	−0.5534 (0.1980) −
$WACH$	−0.6381 (0.0000) ***	−1.0113 (0.0000) ***	−0.8832 (0.0001) ***	−0.1680 (0.4957) −	0.8636 (0.1073) −	—

Table 6: Robustness check results with CRL as the dependant variable

CRA	$CITI$	$BONE$	$MBNA$	$BOAM$	$CHAS$	$WACH$
$CITI$	—	−0.2008 (0.1872) −	−0.3635 (0.1974) −	−0.1007 (0.8695) −	0.4860 (0.4783) −	−0.2035 (0.0542) **
$BONE$	(−1.0722) (0.0000) ***	—	−1.9734 (0.0001) ***	−0.9242 (0.1857) −	−1.4180 (0.3400) −	−2.0595 (0.0020) ***
$MBNA$	3.6483 (0.0359) ##	2.9491 (0.0002) ##	—	2.5454 (0.1204) −	−3.1768 (0.0239) **	3.0033 (0.0042) ###
$BOAM$	−0.2641 (0.0001) ***	−0.1766 (0.3327) −	−0.2096 (0.6343) −	—	0.1882 (0.0000) ###	−0.2622 (0.3464) −
$CHAS$	0.0552 (0.9517) −	−0.1086 (0.8960) −	−0.0981 (0.9315) −	0.0515 (0.6866) −	—	−0.2550 (0.2102) −
$WACH$	−0.4158 (0.0000) ***	−0.6851 (0.0000) ***	−0.5718 (0.0027) ***	−0.0930 (0.4708) −	0.6066 (0.0826) #	—

Table 7: Robustness check results with CRA as the dependant variable

	p**-value**
SI_{CLL}	0.0138
SI_{CRL}	0.0024
SI_{CRA}	0.0085

Table 8: Bootstrap results for robustness check

The main results are similar to Tables 1-3. We can observe from Tables 5-7 the same pattern of competition between Citicorp, Bank One, and Wachovia as in Tables 1-3, while the results involving other banks are mixed.

For the bootstrap the regression is: $y^*_{it} = \alpha x^*_{it} + \beta w^*_{ijt} + \gamma z^*_{jit} + \varepsilon^*_{it}$, , i.e., with the lags of LL_j included in the regression in credit card loan part. The null hypothesis is still:

$$H_0 : y_{it} = \alpha_i x_t + \beta_i w_{it} + u_{it}.$$

with

$$\begin{aligned} y_{it} &= CLL_{it}, CRL_{it}, \text{ or } CRA_{it}, \\ x_t &= (C, T, S_1, S_2, S_3, DPI_t, FFR_t, UMP_t), \\ w_{it} &= (CLL_{it-1}, CLL_{it-2}, CLL_{it-3}, CLL_{it-4}), \end{aligned}$$

The critical values for the chi-squared distribution are: $\chi^2(4)_{0.90} = 7.78$, $\chi^2(4)_{0.95} = 9.49$, and $\chi^2(4)_{0.99} = 13.28$. The sample Significant Indices are: $SI^*_{CLL} = 36$, $SI^*_{CRL} = 28$, and $SI^*_{CRA} = 26$. The p-values are presented in Table 8.

4.1.3 Significance Tests on a 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):

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

This performance difference index measures the average difference of the competing banks' loan performances.[24] For each bank i, we run the following regression:

$$y_{it} = \alpha_i x_t + \beta_i w_{it} + \gamma_i z_{it} + u_{it},$$

where y_{it}, x_t, and w_{it} are the same as before, while $z_{it} = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$. The results are reported in Table 9.

Table 9 presents the average value of the coefficients of z_{ij} and the p-value (in parenthesis) of the Wald test ($\chi^2(4)$), with

$$z_{ijt} = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4}).$$

Table 9 shows that, besides MBNA, all banks have negative and significant coefficients for the performance index, confirming the conjecture from the theory. When there is a large performance difference across all banks, banks raise their lending standards to punish each other, and consequently future loan losses go down.

[24] Again, we first take out the mean from each CLL_i, and then take the difference.

	$y_{it} = CLL_{it}$	$y_{it} = CRL_{it}$	$y_{it} = CRA_{it}$
CITI	−0.7895 (0.2927) –	−2.1500 (0.0073) ***	−0.9752 (0.0758) *
BONE	−1.5211 (0.1038) *	−6.1892 (0.0003) ***	−4.6702 (0.0005) ***
MBNA	0.0631 (0.6693) –	1.3084 (0.3235) –	0.8631 (0.7098) –
BOAM	−0.5212 (0.0354) **	−0.5189 (0.0050) ***	−0.4787 (0.0013) **
CHAS	−0.3860 (0.0873) *	−0.0521 (0.3381) –	−0.1202 (0.1863) –
WACH	−0.4333 (0.0003) ***	−1.4574 (0.0330) **	−0.9755 (0.0458) **

Table 9: Results on performance difference index

4.1.4 A Test of an Alternative Hypothesis

We have asserted that the above results are consistent with our theory, and are not consistent with learning. However, there are some related theories. 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).

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.[25] We construct:

$$\text{Aggregate Credit Card Loan Loss Rate}(AGLL) = \frac{\sum_i (CCO_i - CRV_i)}{\sum_i CLS_i},$$

and we examine the coefficient on $AGLL_{t-1}$ in our regressions:

$$y_{it} = \alpha_i x_t + \beta_i w_{it} + \gamma_i z_t + u_{it},$$

[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.

	$y_{it} = CLL_{it}$	$y_{it} = CRL_{it}$	$y_{it} = CRA_{it}$
CITI	0.6620 (0.0167) –	1.6366 (0.0108) –	0.7115 (0.0441) –
BONE	1.3343 (0.0049) –	4.3686 (0.0020) –	3.3253 (0.0020) –
MBNA	0.0726 (0.3395) –	−1.9956 (0.0028) **	−4.4127 (0.0109) **
BOAM	0.4734 (0.3306) –	0.3611 (0.3016) –	0.3975 (0.1516) –
CHAS	0.0597 (0.7445) –	−0.5579 (0.3238) –	−0.0708 (0.7837) –
WACH	0.3151 (0.1974) –	1.7023 (0.0126) –	1.0373 (0.0312) –

Table 10: Test of alternative hypothesis

where

$$\begin{aligned} y_{it} &\in \{CLL_{it},\, CRL_{it},\, CRA_{it}\}, \\ x_t &= (C, T, S_1, S_2, S_3, DPI_t, FFR_t, UMP_t), \\ w_{it} &= (CLL_{it-1}, CLL_{it-2}, CLL_{it-3}, CLL_{it-4}) \\ z_t &= AGLL_{t-1}. \end{aligned}$$

The coefficients on $AGLL_{t-1}$ and the associated p-value of t-statistics are reported in Table 10.[26]

Table 10 gives out the coefficient on the Aggregate Credit Card Loan Loss ($AGLL$) and the p-value of t-statistics, with other macroeconomic variables in the regressors. Rajan's (1994) idea is that an aggregate bad shock leads banks to raise their standards, so we would expect the coefficients on $AGLL_{t-1}$ to be significantly negative. However, as the table shows, conditional on other macroeconomic variables, besides bank 3, the coefficients of the aggregate loan loss rate are all positive, and some of them are significant; this is the result of the persistence of loan loss and asset allocation.

If we remove other macroeconomic variables from the regression, i.e.,

$$x_t = (C, T, S_1, S_2, S_3, AGLL_{t-1}),$$

results are basically the same.

4.1.5 Stock Return Prediction

Strategic competition between banks results in periodic credit crunches, an aggregate of systematic risk. Consequently, if the stock market is efficient, then the stock returns of each bank holding company should

[26] Adding more lags of $AGLL$ gives us basically the same results.

Beta	β_1	β_2	β_3	β_4		
$coeff.$ $(t-stat)$	3.4311 (0.9155) $-$	-2.4101 (-0.6376) $-$	-5.9428 (-1.5715) $-$	-13.665 (-3.6136) ***		
Intercept	α_1	α_2	α_3	α_4	α_5	α_6
$coeff.$ $(t-stat)$	0.1138 (3.5323) ***	0.0247 (1.0237) $-$	0.0944 (3.6143) ***	0.0450 (2.1519) **	0.0842 (2.7509) ***	0.0296 (2.2020) **

Table 11: Results on stock returns with six banks

Beta	β_1	β_2	β_3	β_4
$coeff.$ $(t-stat)$	1.9495 (0.4902) $-$	-0.4509 (-0.1124) $-$	-7.7452 (-1.9304) *	-11.990 (-2.9885) ***
Intercept	α_2	α_3	α_6	
$coeff.$ $(t-stat)$	0.0248 (1.0519) $-$	0.0944 (3.7058) ***	0.0297 (2.1434) **	

Table 12: Results on stock returns with three banks

reflect the competition between banks. In this section, we test 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 return from CRSP from 1991.I to 2000.IV. During this period, Citicorp, Bank of America, and Chase Manhattan are involved in mergers.[27] We carry out the tests for all six bank holding companies and for the three bank holding companies (Bank One, MBNA, and Wachovia) without merger activity. According to our theory, after observing large performance differences between banks, banks will raise their lending standards (which is costly) and consequently their profit margins will be lower. Therefore, we expect to see negative loadings on the lags of the performance difference index. The regression equations are:

$$r_{it} = a_i + \beta_{i1}PDI_{t-1} + \beta_{i2}PDI_{t-2} + \beta_{i3}PDI_{t-3} + \beta_{i4}PDI_{t-4} + \varepsilon_{it},\ i = 1, 2, ..., 6 \text{ (or } i = 2, 3, 6).$$

We use the Seemingly Unrelated Regression method to estimate the system of equations, with the restriction that the β_is are the same across banks (we only allow for different intercepts).[28] The results are reported in Table 11 for the case with six banks and in Table 12 for the case with three banks.

Table 11 gives out the results about the prediction power (on stock returns) of the performance difference index with six bank holding companies, and Table 12 gives out the results three bank holding companies. From both Table 11 and Table 12, we see that the performance difference index from the previous year significantly predicts the stock return this period. For the case with six banks, the Wald test of $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ gives $\chi^2 = 20.6229$, with p-value 0.0004. For the case with three banks, the Wald test of $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ gives a $\chi^2 = 10.2850$, with p-value 0.0359. Therefore, the performance difference index that we constructed does have some prediction power for the stock return.

[27] The dates of the M&A activity are: Citigroup,1998.10; Bank of America, 1998.10; and Chase Manhattan in 1996.4.

[28] In the regressions, we take out the mean and the seasonal effects for the first three quarters from the performance difference index (PDI).

Beta	β_1	β_2	β_3	β_4		
$coeff.$ $(t-stat)$	4.1728 (1.0666) –	−1.7792 (−0.4581) –	−6.2940 (−1.6282) *	−13.557 (−3.4539) ***		
Intercept	α_1	α_2	α_3	α_4	α_5	α_6
$coeff.$ $(t-stat)$	0.0626 (1.5942) *	−0.1061 (−1.2727) –	0.1078 (2.4689) **	−0.0214 (−0.2797) –	−0.0276 (−0.4338) –	−0.0401 (−0.7018) –
Gama	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6
$coeff.$ $(t-stat)$	3.4921 (2.0434) **	3.7721 (1.6351) *	−0.5255 (−0.3815) –	2.3147 (0.9040) –	3.4264 (1.9423) *	2.2451 (1.2553) –

Table 13: Results on stock returns with dividend yield, six banks

Beta	β_1	β_2	β_3	β_4
$coeff.$ $(t-stat)$	2.4851 (0.6147) –	0.2885 (0.0721) –	−7.3791 (−1.8517) *	−12.322 (−3.0404) ***
Intercept	α_2	α_3	α_6	
$coeff.$ $(t-stat)$	−0.0820 (−0.9396) –	0.0811 (1.6230) *	−0.0232 (−0.3750) –	
Gama	γ_2	γ_3	γ_6	
$coeff.$ $(t-stat)$	3.0793 (1.2676) –	0.5265 (0.3123) –	1.7038 (0.8776) –	

Table 14: Results on stock returns with dividend yield, three banks

Since dividend yield is well known to be a good predictor for the future stock return (see, e.g., Cochrane (1999)), we also include dividend yields in the regressions. We collect the dividends of each bank from CRSP. The quarterly dividend yield is constructed as follows: We first construct the monthly dividend yield using the dividends during past twelve months divided by the stock price at the end of the month; then we take the three-month average to get the quarterly dividend yield.[29] The regression equations are:

$$\begin{aligned} r_{it} &= a_i + \beta_{i1}PDI_{t-1} + \beta_{i2}PDI_{t-2} + \beta_{i3}PDI_{t-3} + \beta_{i4}PDI_{t-4} + \gamma_i DY_{it-1} + \varepsilon_{it}, \\ \text{for } i &= 1, 2, ..., 6 \text{ (or } i = 2, 3, 6). \end{aligned}$$

Again, we use the Seemingly Unrelated Regression method to estimate the equation system with the restriction that β_is are the same across banks (we only allow for different intercepts). The results are reported in Table 13 for the case with six banks and in Table 14 for the case with three banks.

Table 13 gives out the results about the prediction power (on stock return) of the performance difference index with six bank holding companies while we include dividend yield as another prediction variable, and

[29] The time series of MBNA start from January of 1991. So, to calculate the dividend yield of 1991, we use dividends in 1991 as a proxy of dividends in 1990.

Table 14 gives out the results with three banks. Again, from both Table 13 and Table 14, we can observe that the lagged performance difference index significantly predicts the stock return this period. For the case with six banks, the Wald test of $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ gives $\chi^2 = 19.103$, with p-value 0.0008. For the case with three banks, the Wald test of $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ gives a $\chi^2 = 16.147$, with p-value 0.0028.

4.2 VAR Analysis of the Fed's Lending Standards Index

If banks raise their increase their information production, raise their lending standards, then some borrowers are cut off from credit, a credit crunch that should have macroeconomic implications. In this section, 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 is a system of equations that lets us better control for the feedback between current and past levels of performance differences, the lending standard survey, and macro 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 predict, in the sense of Granger causality, the index of lending standards based on the Federal Reserve System's Senior Loan Officer Opinion Survey on Bank Lending Practices. We follow Lown and Morgan (2001, 2002) and Schreft and Owens (1991) in analyzing the time series of survey responses, the percentage of banks reporting tightening in the survey. The series starts from the first quarter of 1967, and it ends at the last quarter of 2001. However, in 1984 the question on credit standards was dropped from the survey, and then was reintroduced starting from the second quarter of 1992.

As above, we use quarterly bank loan data from the Chicago Federal Reserve Bank's Commercial Bank and Bank Holding Company Database, which is from the Call Reports. For the period from 1976.1 to 2002.2, we collected Total Loans, Net of Unearned Income (TL); Loan Loss Allowances (LA). For each bank (holding company) we constructed the Loan Loss Allowance Ratio (LAR):

$$LAR = \frac{LA}{TL}.$$

We construct the Performance Difference Index to measure the dispersion of performance across the U.S. banking industry as a whole. To do this, we use the top 200 commercial banks ranked by total loans, and for each period, we construct the Performance Difference Index as follows:[30]

$$PDI = \frac{\sum_{i>j} |LAR_i - LAR_j|}{19900}.$$

Besides the data on the Lending Standards and the Performance Difference Index, we also collected data on Total Loans and Leases at Commercial Banks and Federal Funds Rate.[31]

We conjecture that this Performance Difference Index captures the relevant history that is at the basis of banks' beliefs about whether other banks are deviating to using the credit worthiness tests.[32]

4.2.1 VAR Results

The VAR includes four lags of the four endogenous variables: bank lending standards ($STAND$) (i.e., the survey responses), the performance difference index (PDI), the federal funds rates (FFR), and the log of

[30] Some banks report the loan loss or loan allowance semi-annually instead of quarterly, so we drop these zero value in the calculation below, therefore, the denominator is not necessarily 19900.

[31] We first collected monthly data, then we took the three-month average to obtain quarterly data.

[32] We also constructed the performance difference index using charge-off ratios. The empirical results are similar, and are omitted to save space.

	STAND LAGS	PDI LAGS	FFR LAGS	LOGLOAN LAGS
STAND	0.1981 (0.0020) ***	498.82 (0.0077) ***	−1.2523 (0.0010) **	30.464 (0.1673) –
PDI	−4.1E-6 (0.7414) –	0.1309 (0.0411) **	−0.0001 (0.3452) –	0.0076 (0.7480) –
FFR	−0.0066 (0.0127) **	−101.60 (0.0006) ***	0.0414 (0.0000) ***	7.6086 (0.0032) **
LOGLOAN	−9.3E-6 (0.0172) **	0.3515 (0.0267) **	0.0012 (0.0000) ***	0.2051 (0.0000) **

Table 15: Results for VAR analysis

commercial bank loans ($LOGLOAN$). Bank lending standards are a loan supply side factor and the federal funds rate is a loan demand side; commercial bank loans are the equilibrium outcomes, and the performance difference index captures the market beliefs, which affect all the other variables. The exogenous variables are a constant, a time trend, and seasonal dummies for the first three quarters of a year.

We run the VAR for the period of 1990.II–2001.IV, which is the longest continuous of period where both $STAND$ and PDI have data. The results are presented in Table 15.

Table 15 presents the average value of the coefficients and P-values (in parenthesis) of the Wald test ($\chi^2(4)$) of VAR with four lags of the lending standards, the performance difference index, log commercial bank loans, and federal funds rate. Table 15 shows that the Performance Difference Indices Granger-causes all the other three endogenous variables, but not vice versa. An increase in PDI immediately causes a rise of $STAND$, which triggers a "recession," and thus leads to a future decrease in the FFR, and a future decrease of in $LOGLOAN$ (even though the average value of coefficients of PDI for equation $LOGLOAN$ is positive, the only significant one is negative). We can clearly observe this pattern in the graph of impulse responses in Figure 4.

The results support the theoretical prediction, namely, that strategic bank competition is an autonomous driving force of the macro dynamics. The performance difference index is a predictor of bank lending behavior, and thus implicitly a sufficient measure of public histories upon which banks' beliefs are based.

4.3 Risk-Factor Analysis

If strategic behavior between banks causes credit cycles, then it causes variation in the profitability of banks. Credit crunches are not profitable for banks. The credit cycle is a systematic risk. We conjecture that the constructed performance difference indices should be a priced risk factor for the banking industry. That is, in an asset pricing model of bank stock returns, there should be an additional factor, namely, the performance difference index. We adopt the widely-used Fama-French three factor empirical asset pricing model, augmented with a momentum factor (as has become common practice).[33] The asset pricing regression

[33] See Fama and French (1993, 1996). Carhart (1997) introduced the momentum factor. We collect the quarterly Fama-French three factors and momentum factor from French website (the construction method can also be found there). The quarterly bank returns are collected from COMPUSTAT. The data that we use range from 1993.II to 2001.IV, and there are

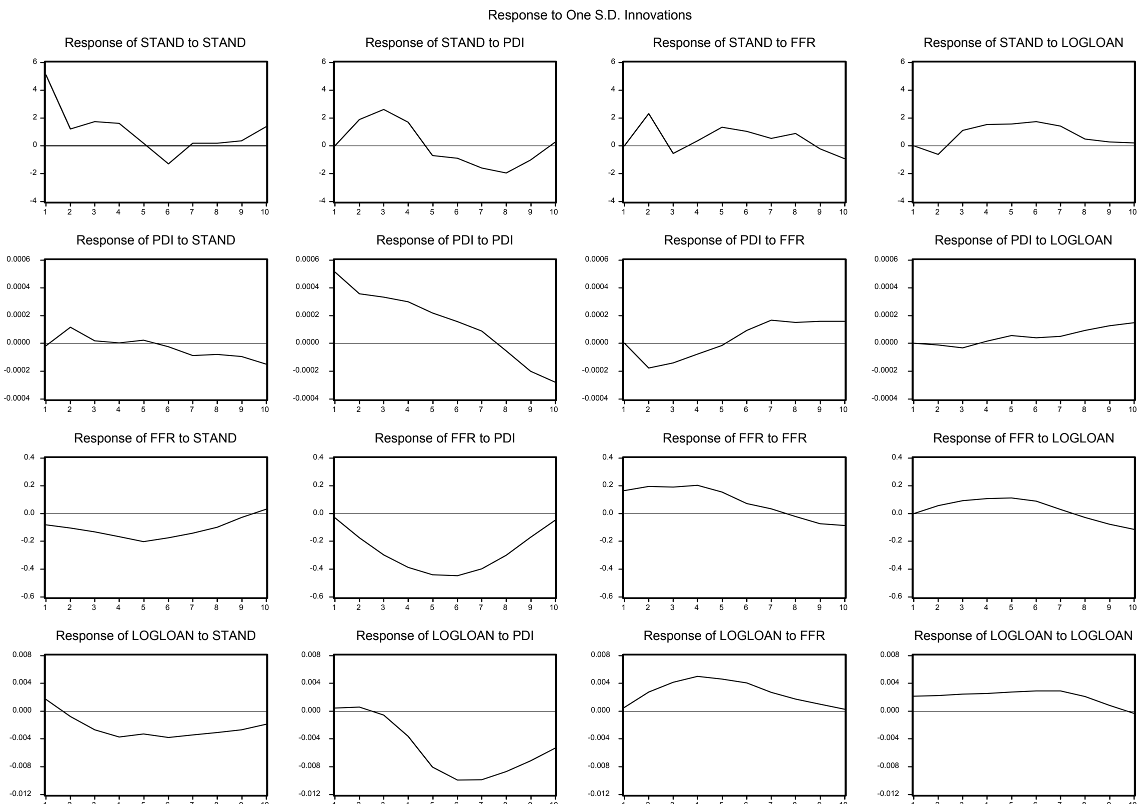

Figure 4: This figure gives the impulse response of VAR analysis.

	β_i (t-statistics)
c	-2.0330 (-10.8786)***
$r_m - r_f$	0.6962 (27.316)***
SMB	0.3621 (14.559)***
HML	0.9345 (32.497)***
MOM	0.4728 (17.071)***
PDI	418.16 (3.5058)***

Table 16: Results for risk-factor analysis

results are reported in Table 16.[34]

Table 16 reports the coefficients and t-statistics of the factor-regression with $r_m - r_f$, SMB, HML, MOM and PDI as the risk factors. The results in Table 16 show that the performance indices are significant risk factors. The mean of PDI is 0.0110, and the standard deviation is 0.00133. Therefore, when the performance index changes by one standard deviation, the excess return changes by about 50 basis points. We conclude that the competition and collusion among banks is an important risk factor for bank returns.

5 Conclusion

Banking is special because banks produce information about lenders and therefore are, themselves, repositories of private information. This role of banks makes them opaque institutions, subject to banking panics and consequently government insurance. In this paper we show that this basic feature of banking extends to banks themselves when they compete for lenders. Banks compete imperfectly because of restricted entry. Imperfect competition leads banks to behave strategically and we showed that this endogenously causes credit cycles. Credit crunches due to bank competition are an important part of business cycle dynamics.

The theory predicts public information about bank lending performance is the basis for banks' beliefs, changes in which cause credit cycles. Empirically we showed that a simple parameterization of relative bank performance differences has predictive power for rival banks in the credit card market. Moreover, introducing the performance difference histories into a vector autoregression-type macroeconomic model confirms that this is an autonomous source of macroeconomic fluctuations. Since changes in bank beliefs based on public information cause credit cycles, this should be an important independent risk factor for bank stock returns. We showed that this is indeed the case.

18708 bank-quarters in total (about 700-800 banks). The risk free rates are three-month T-Bill rates (we take the average of monthly data to get the quarterly data) from FRED II at Federal Reserve Bank at St. Louis.

[34] We demean PDI.

Appendix 1: Proofs

Before we prove Proposition 1, we first prove the following two lemmas.

Lemma 3 *If it exists, in any symmetric stage Nash equilibrium in which neither bank conducts credit worthiness tests, each bank offers loans to all the loan applicants.*

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. ■

Lemma 4 *If it exists, in any symmetric stage Nash equilibrium in which neither bank conducts credit worthiness tests, each bank offers the same interest rate to all the applicants.*

Proof. Let F^* be the interest rate corresponding to zero profits in the loan market when there is no testing. Then:

$$\begin{aligned} E\pi_i &= \frac{N}{2}[\lambda p_b F^* + (1-\lambda)p_g F^* - 1] = 0, \\ \text{and } F^* &= \frac{1}{\lambda p_b + (1-\lambda)p_g} < X \text{ (by Assumption 1).} \end{aligned}$$

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 $F_j \geq F^*$ for $j = 1, 2, ..., N$ and assume there exist j and k, such that $F_j \neq F_k$, 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 Lemmas 3 and 4, we see that in a symmetric equilibrium with no bank testing applicants, both banks offer loans to all the applicants at $F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g} < X$ (by Assumption 1).

With $c < \frac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$, a bank will have an incentive to carry out the credit worthiness test 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 carrying out the credit worthiness test on one applicant. The expected profit from this deviation is:

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

We can see that:

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

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

Before we prove Proposition 2, we first state the following two lemmas.

Lemma 5 *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.*

The proof is similar to Lemma 3 and is omitted.

Lemma 6 *In any symmetric stage Nash equilibrium in which both banks test all the applicants, each bank offers the same interest rate to all the applicants that pass the test.*

The proof is similar to Lemma 4 and is omitted.

Proof. (Proposition 2) The proof is by contradiction. If there exists a Nash equilibrium with both banks carrying out the credit worthiness test on all the applicants, from Lemmas 5, 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, i.e., $N_\gamma = 0$. Both banks use the credit worthiness test at a cost c per applicant. Based on Lemma 6, 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 $\frac{1}{2}N_g$ applicants. Let p_k denote the probability of finding k good type applicants. Then:

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

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

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

■

Before we prove Proposition 3, we first prove the following two lemmas.

Lemma 7 *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 $F^{**} = \frac{1}{p_g}$.*

Proof. First, notice that the two banks might choose different sets of n applicants for testing due to random selection. If one bank's strategy is ($n < N$, N_α, N_β, F_α, F_β), where $F_\beta = \{F_1, ..., F_{N_g}\}$, then we can see that $F_k \geq F^{**} = \frac{1}{p_g}$, for any $k = 1, ..., N_g$. If there exist $i, j < N_g$, $F_i \neq F_j$, then there exists some $F_k \in F_\beta$, and $F_k > F^{**}$, so bank i can strictly improve its profitability by setting $F'_\beta = \{F_k^-, F_{-k}\}$, where F_k^- is smaller than F_k by an infinitely small amount and $F_{-k} = \{F_1, ..., F_{k-1}, F_{k+1}, ..., F_{N_g}\}$. It is easy to check that by lowering F_k, the marginal cost is close to zero, while the marginal gain is substantial. By lowering F_k, conditional on that bank already winning the applicant, the only cost of lowering F_k is a small decrease in profit, while the marginal gain, the probability of winning the applicant, is substantially improved. ■

Lemma 8 *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 $F \leq X$ 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 3, we conclude that each bank offers loans to all non-tested applicants. Assume $F_\alpha = \{F_1, ..., F_{N_\alpha}\}$, where $N_\alpha \leq N - n$, then offering F_α to non-tested applicants results in a non-negative profit.[35] Let us assume that the minimum interest rate on loans to non-tested applicants to insure non-negative profit is $F(n)$. If there exists $i, j < N - n$, $F_i \neq F_j$, then there exists some $F_k \in F_\alpha$, and $F_k > F(n)$, so bank i can strictly improve its profitability by setting $F'_\alpha = \{F_k^-, F_{-k}\}$, where F_k^- is smaller than F_k by an infinitely small amount and $F_{-k} = \{F_1, ..., F_{k-1}, F_{k+1}, ..., F_{N_\alpha}\}$. It is easy to check that by lowering F_k, the marginal cost is close to zero, while the marginal gain is substantial. By lowering F_k, conditional on that bank already winning the applicant and the applicant is of good type, based on being tested by the other bank or the applicant has not been tested by either bank, the cost of lowering F_k is a small decrease in profit. But conditional on the applicant being a bad type that was tested and rejected by the other bank, the cost is an even smaller decrease in profit. The marginal gain of the probability of winning the applicant when the applicant is either non-tested or is a good type (that was tested by the other bank), is substantially improved.

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.[36] ■

Proof. (Proposition 3) For the case in which 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.

For the case in which 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. ■

Proof. (Proposition 4) The proof is by contradiction. 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 $F^* = \frac{1}{\lambda p_b + (1-\lambda) p_g}$, and the continuation value function does not depend on (χ_1, χ_2), i.e., the number of defaulted loans in each bank's loan portfolio.

To eliminate the incentive for a bank to deviate to strategy $s'(D) = (n = 0,\ N_\alpha = D,\ F_\alpha^-)$, for some $0 \leq D \leq N$, we must have:

$$\begin{aligned} & E[\pi_1(s'(D), s) + \delta u_1(D, N - D)] \\ = \quad & E[\pi_1(s'(D'), s) + \delta u_1(D', N - D')] \text{ for any } D \neq D'. \end{aligned}$$

[35] Here we can not say that the profitable level of the loan face value is $F^* = \frac{1}{\lambda p_b + (1-\lambda) p_g}$, since the $N - n$ non-testedapplicants for one bank might contain some bad type borrowers rejected by the other bank.

[36] 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 exists 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 3.

[37]

Moreover, due to symmetry, it is easy to see that:

$$\begin{aligned} & \delta E[u_1(D, N-D)] - \delta E[u_1(D+1, N-D-1)] \\ = \quad & [\lambda p_b + (1-\lambda)p_g]F_\alpha - 1 \text{ for any } D. \end{aligned} \tag{4}$$

Let us first take a look at an example with two loan applicants and consider a deviation to strategy s'' in which a bank tests one applicant. If the tested applicant is a bad type the bank rejects it and, without testing the other applicant, undercuts the interest rate to F_α^- for the loans to the other applicant. If the tested applicant is of good type then the bank offers a loan to the applicant at F_α^- and raises the interest rate to F_α^+ for the loan to (or rejects) all other applicants, without testing them. In this way the expected loan portfolio size for both banks will remain the same while the distribution of the loan portfolio size changes a little. It is easy to check that the improvement in the stage profit for the deviating bank is:

$$\Delta E[\pi] = -c + \lambda(1-\lambda)(p_g - p_b)F_\alpha,$$

and and $\Delta E[\pi] > 0$ iff $c < \lambda(1-\lambda)(p_g - p_b)F_\alpha$.

Recall Assumption 2: $c \geq \frac{(1-\lambda)\lambda(p_g-p_b)}{\lambda p_b+(1-\lambda)p_g}$. Therefore, the parameter space is not empty as long as:

$$F_\alpha > F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g}.$$

In our example with two loan applicants, if one bank deviates in the way we described above, then the loan allocation is $(1,1)$ with probability 1, while without a deviation, the loan allocation is $(2,0)$ with probability $\frac{1}{4}$, $(1,1)$ with probability 1, and $(0,2)$ with probability $\frac{1}{4}$. We know by (4):

$$Eu_1(0,2) - Eu_1(1,1) = Eu_1(1,1) - Eu_1(2,0),$$

which implies:

$$\frac{1}{4}Eu_1(0,2) + \frac{1}{2}Eu_1(1,1) + \frac{1}{4}Eu_1(2,0) = Eu_1(1,1).$$

Thus with the deviation s'', the expected continuation payoff remains unchanged.

For more general case with more than two loan applicants, suppose that one bank deviate in the way above. Let $p_{k,N-k}$ denote the probability of $(k, N-k)$ for the two banks' loan portfolio sizes when no bank deviates, and $p'_{k,N-k}$ as the probability of $(k, N-k)$ for the two banks' loan portfolio size with the deviation. By symmetry, it is easy to check that:

$$\sum_k p_{k,N-k} E[u_i(k, N-k)] = \sum_k p'_{k,N-k} E[u_i(k, N-k)] \text{ for bank } i = 1, 2.$$

There is a stage profit improvement, while the expected continuation value remains the same, a contradiction. ■

Proof. (Corollary 1) The proof is similar to that of Proposition 4. First consider the case $N-2 \geq N_\alpha$. 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 $F^* = \frac{1}{\lambda p_b+(1-\lambda)p_g}$, and the continuation value function does not depend on (χ_1, χ_2), i.e., the number of defaulted loans in each bank's loan portfolio.

[37] 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.

Denote $s'(D) = (n = 0,\ N_\alpha = D,\ F_\alpha^-)$ as a feasible deviation strategy, for some $0 \leq D \leq N_\alpha$. Let $\overline{N}(D)/\underline{N}(D)$ be the maximum/minimum possible number of applicants that accept loans offered by bank 2 when bank 1 deviates to $s'(D)$, and let $p_k(D)$ be the probability of bank 2 getting k applicants given bank 1 getting D applicants. We must have:

$$\begin{aligned} & E[\pi_1(s'(D), s) + \delta \sum_{k=\underline{N}(D)}^{\overline{N}(D)} p_k(D) u_1(D, k)] \\ = \quad & E[\pi_1(s'(D'), s) + \delta \sum_{k=\underline{N}(D')}^{\overline{N}(D')} p_k(D') u_1(D', k)] \text{ for any } D \neq D', \end{aligned}$$

which implies:

$$\begin{aligned} & \delta E \sum_{k=\underline{N}(D)}^{\overline{N}(D)} p_k(D) u_1(D, k) - \delta \sum_{k=\underline{N}(D-1)}^{\overline{N}(D-1)} p_k(D-1) u_1(D-1, k)] \\ = \quad & [\lambda p_b + (1-\lambda) p_g] F_\alpha - 1 \text{ for any } D. \end{aligned} \tag{5}$$

Consider the following deviation in which one bank tests one applicant. If the tested applicant is good, then it offers loan to this tested applicant at F_α^-, offers loan to a randomly picked non-tested applicant at F_α^+, and offers loans to other randomly picked $N_\alpha - 2$ applicants at F_α. If the tested applicant is bad, it rejects the applicant, and offers loan to other randomly picked N_α applicants at F_α. We denote the above deviating strategy as s''. We can check that given (5), s'' gives the same expected continuation payoff as s.

The improvement in the stage profit for the deviating bank can be written as:

$$\Delta E[\pi] = -c + \lambda(1-\lambda)(p_g - p_b) F_\alpha,$$

and the result comes out immediately.

The proof for the case with $N_\alpha = N - 1$ is similar, and thus omitted. ∎

Proof. (Corollary 2) For the case with $N = N_\alpha$, consider the deviation in which one bank tests one applicant and offers loan to that applicant at $\min\{F_\alpha\}^- > F^*$ with probability $\frac{2N-1}{2N}$when it is good and rejects the applicant when it is bad. We can check this keep the distribution (D_1, D_2) the same, and thus the continuation payoff is the same with the deviation. The stage gain is $c - \frac{2N-1}{2N} \lambda(1-\lambda)(p_g - p_b) \min\{F_\alpha\}$.

For the case with $N < N_\alpha$, consider the deviation in which one bank tests one applicant and offers loan to that applicant at $\min\{F_\alpha\}$ when it is good, when it is bad, rejects the applicant and picks another un-tested applicant to keep the total number of applicants it approves the same. We denote the above deviating strategy as s'. Denote $\pi(s, s)$ as $\pi(N, N_\alpha)$, and it is easy to understand what $\pi(N-1, N_\alpha - 1)$ means; we also denote $\pi(N-1, N_\alpha - 1, N_\alpha)$ as the expected payoff of one bank offering loans to $N_\alpha - 1$ applicants out of $N - 1$, while the other banks offers to N_α of them. It is easy to check that with the deviation to s', the deviating bank's expected payoff is:

$$\begin{aligned} \pi' \quad = \quad & (1-\lambda)\{(\frac{1}{N}\frac{1}{2} + \frac{N_\alpha - 1}{N})(p_g \min\{F_\alpha\} - 1) + \frac{N_\alpha}{N}\pi(N-1, N_\alpha - 1) \\ & + \frac{N - N_\alpha}{N}[(p_g \min\{F_\alpha\} - 1) + \pi(N-1, N_\alpha - 1, N_\alpha)]\} + \lambda \pi(N, N_\alpha) - c. \end{aligned}$$

We can also write $\pi(N, N_\alpha)$ as follows:

$$\begin{aligned} \pi(N, N_\alpha) \quad = \quad & (\frac{1}{N}\frac{1}{2} + \frac{N_\alpha - 1}{N})[(1-\lambda)p_g \min\{F_\alpha\} + \lambda p_b \min\{F_\alpha\} - 1] + \frac{N_\alpha}{N}\pi(N-1, N_\alpha - 1) \\ & + (1 - \frac{N_\alpha}{N})\{[(1-\lambda)p_g \min\{F_\alpha\} + \lambda p_b \min\{F_\alpha\} - 1] + \pi(N-1, N_\alpha - 1, N_\alpha)\}. \end{aligned}$$

We have:

$$
\begin{aligned}
\pi' - \pi(N, N_\alpha) &= (1-\lambda)\{(\frac{1}{N}\frac{1}{2} + \frac{N_\alpha - 1}{N})\lambda(p_g - p_b)\min\{F_\alpha\}] + (1 - \frac{N_\alpha}{N})\lambda(p_g - p_b)\min\{F_\alpha\}\} - c \\
&= \frac{2N-1}{2N}\lambda(1-\lambda)(p_g - p_b)\min\{F_\alpha\} - c > 0 \\
\text{iff } c &< \frac{2N-1}{2N}\lambda(1-\lambda)(p_g - p_b)\min\{F_\alpha\}.
\end{aligned}
$$

■

Appendix 2: An Example of a PPE with Trigger Strategies

In this example, for simplification, banks start with asymmetric strategies to reach a symmetric loan distribution. Assume that each period there are two loan applicants ($N = 2$). Banks want to keep the loan interest rate at $F = X$. The loan portfolio size distribution for the two banks is determined as follows. When there is no credit worthiness testing, Bank 1 offers loans to both applicants at interest rate X, while Bank 2 offers a loan to only one applicant at interest rate X^-, and rejects the other applicant. Each bank will get exactly one loan in equilibrium. They punish any other loan distribution by playing stage Nash equilibrium forever.

Formally, the period one strategy for Bank 1 is $s_1 = (n = 0,\ N_{\alpha 1} = 2,\ F_{\alpha 1} = X)$; Bank 2's strategy is $s_2 = (n = 0,\ N_{\alpha 2} = 1,\ F_{\alpha 2} = X^-)$. For a discount rate, δ, close enough to 1, Bank 1 does not have an incentive to deviate by conducting credit worthiness testing, since if Bank 1 rejects one bad-type applicant, while Bank 2 offers loans to the other one, there will be a positive possibility that the loan distribution will be different from $(1,1)$.[38] However, with the above strategy Bank 2 might have an incentive to carry out testing while keeping the loan distribution equal to $(1,1)$ with probability 1. With δ close enough to 1, the only possible deviation, without changing the loan portfolio distribution, is as follows. Bank 2 deviates to high credit standards by testing one of the applicants. After carrying out the test, if the tested applicant is of bad type, then Bank 2 offer a loan to the non-tested applicant at X^- while rejecting the other one; if the tested applicant is of good type, Bank 2 offers a loan to it at X^- while rejecting the other one. Formally Bank 2's deviation strategy can be written as $s_2' = (n = 1,\ N_{\alpha 2}(N_g),\ N_{\beta 2}(N_g),\ F_{\alpha 2} = F_{\beta 2} = X^-)$, where:

$$\begin{aligned} N_{\alpha 2}(N_g) &= 1, \text{ if } N_g = 0 \\ N_{\beta 2}(N_g) &= 1, \text{ if } N_g = 1. \end{aligned}$$

We claim that if X is big enough, then Bank 2 will be strictly better off by deviating for some level of test cost c. When Bank 2 does not deviate, the expected stage payoff is:

$$E\pi_2 = \lambda(p_b X - 1) + (1-\lambda)(p_g X - 1).$$

When Bank 2 deviates as described above, the expected stage payoff is:

$$E\pi_2' = (1-\lambda)(p_g X - 1) + \lambda[(1-\lambda)(p_g X - 1) + \lambda(p_b X - 1)] - c.$$

We have:

$$\begin{aligned} E\pi_2' - E\pi_2 &= \lambda(1-\lambda)(p_g - p_b)X - c \\ &> 0 \\ iff \quad c &< \lambda(1-\lambda)(p_g - p_b)X \end{aligned}$$

Compare this condition with that of Assumption 2: $c \geq \frac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$. As long as $X > F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g}$, the parameter space is not empty.

[38] It can be verified that other forms of deviation are also not incentive compatible for Bank 1.

However, with a trigger punishment, we can eliminate the incentive of Bank 2 to deviate through credit worthiness testing. The idea is for both banks to test all applicants for T periods whenever Bank 1's borrower defaults while Bank 2's borrower does not. When both banks test, if there is no bad-type applicant, Bank 1 offers loans to both applicants at X, and Bank 2 offers a loan to one applicant at X^-. If there is one good-type applicant, only Bank 1 offers a loan to the good type applicant at X, while Bank 2 rejects all the applicants. Finally, if there are two bad-type applicants, both banks reject all the applicants.

Now, we are ready to describe a trigger strategy that will support the PPE. At period $t = 0$, Bank 1's strategy is $s_1 = (n = 0,\ N_{\alpha 1} = 2,\ F_{\alpha 1} = X)$, and Bank 2's strategy is $s_2 = (n = 0,\ N_{\alpha 2} = 1,\ F_{\alpha 2} = X^-)$. At $t > 0$, they will continue to play (s_1, s_1) unless one of the following two cases occurred at $t - 1$:

(1) If they observe $(D_{1t-1}, D_{2t-1}) \neq (1, 1)$, then they play (s^d, s^d) for the rest of the periods, where $s^d = (n = 0,\ N_\alpha = 2, F_\alpha = F^*)$.

(2) Else, if they observe $\chi_{1t-1} = 0$ and $\chi_{2t-1} = 1$, then they play (s_1^r, s_1^r) at period t, where $s_1^r = (n = 2,$ $N_{\beta 1}(N_{gt}),\ N_{\gamma 1}(N_{gt}) = 0,\ F_{\beta 1} = F_{\gamma 1} = X)$, $s_2^r = (n = 2,\ N_{\beta 2}(N_{gt}), N_{\gamma 2}(N_{gt}) = 0,\ F_{\beta 2} = F_{\gamma 2} = X^-)$ and

$$
\begin{aligned}
N_{\beta 1}(N_{gt}) &= 2 \text{ if } N_{gt} = 2 \\
&= 1 \text{ if } N_{gt} = 1 \\
&= 0 \text{ if } N_{gt} = 0 \\
N_{\beta 2}(N_{gt}) &= 1 \text{ if } N_{gt} = 2 \\
&= 0 \text{ if } N_{gt} = 1 \\
&= 0 \text{ if } N_{gt} = 0.
\end{aligned}
$$

They will continue to play (s_1^r, s_2^r) unless one of the following two cases occurs at $\tau > t$:

(2.1) If banks do not observe $(1, 1)$, $(1, 0)$, or $(0, 0)$,[39] then they will play (s^d, s^d) for the rest of the time, where $s^d = (n = 0,\ N_\alpha = 2, F_\alpha = F^*)$.

(2.2) Else, if $\tau \geq t + T$, i.e. T periods have elapsed, then the banks go back to normal by playing (s_1, s_2) as defined above.

Formally, the trigger strategy is defined as follows. Define period t to be *normal* if (a) $t = 0$; or (b), $t - 1$ was normal, $D_{t-1} = (1, 1)$ and $\chi_{1t-1} = 1$; or (c), $t - T - 1$ was normal, $D_{t-1} = (D_1(N_{gt-1}), D_2(N_{gt-1}))$, and $t - 1$ was reversionary (as we will define in a moment). Define period t to be *reversionary* if (a) $t - 1$ was normal, $D_{t-1} = (1, 1)$ and $\chi_{1t-1} = 0$; or (b), $t - 1$ is reversionary, and $t < T$ or else $t - T$ is normal, and $D_{t-1} = (D_1(N_{gt-1}), D_2(N_{gt-1}))$. Define period t to be *devastating* otherwise. Let s_t be the strategy for banks, and the trigger strategy is given by:

$$
s_t = \begin{cases} (s_1, s_2) & \text{if } t \text{ is normal} \\ (s_1^r, s_2^r) & \text{if } t \text{ is reversionary} \\ (s^d, s^d) & \text{if } t \text{ is devastating.} \end{cases}
$$

Each bank faces a stationary Markov dynamic programming problem. Its optimal strategy is to play (s_1, s_2) in normal periods, play (s_1^r, s_2^r) in reversionary periods, and play (s^d, s^d) in deviating periods. The

[39] In fact, (D_1, D_2) depends on $N_{g\tau-1}$, which is not public information, we have, on the equilibrium path,

$$
\begin{aligned}
& (D_1(N_{g\tau-1}), D_2(N_{g\tau-1})) \\
= & \ (1, 1) \text{ if } N_{g\tau-1} = 2 \\
= & \ (1, 0) \text{ if } N_{g\tau-1} = 1 \\
= & \ (0, 0) \text{ if } N_{g\tau-1} = 0.
\end{aligned}
$$

In PPE, however, banks' strategies can not depend on non-public information.

play (s^d, s^d) is a threatening play, which will never occur on the equilibrium path, while both (s_1, s_2) and (s_1^r, s_2^r) will occur.

If t is a normal period, and banks play (s_1, s_2), then the probability of switching to a reversionary period at time $t+1$ is:

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

With bank 2 deviating to s_2', We have:

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

However, if one Bank 2 plays $s_2' = (n = 1,\ N_{\alpha 2}(N_g),\ N_{\beta 2}(N_g),\ F_{\alpha 2} = F_{\beta 2} = X^-)$ where:

$$\begin{aligned} N_{\alpha 2}(N_g) &= 1, \text{ if } N_g = 0 \\ N_{\beta 2}(N_g) &= 1, \text{ if } N_g = 1, \end{aligned}$$

this probability becomes:

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

We can see that:

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

In words, the above condition says that when Bank 2 deviates to s_2', the probability of switching to a reversionary period increases. By hypothesis Bank 2 is deviating. Now, having defined the trigger strategies, we check the incentive constraint for Bank 2. In the normal period, Bank 2's expected stage payoff from playing $s_2 = (n = 0,\ N_{\alpha 2} = 1,\ F_{\alpha 2} = X^-)$ given $s_1 = (n = 0,\ N_{\alpha 1} = 2,\ F_{\alpha 1} = X)$ is:

$$E\pi_2^n = \lambda(p_b X - 1) + (1-\lambda)(p_g X - 1).$$

In the reversionary period, Bank 2's expected stage payoff from playing $s_2^r = (n = 2,\ N_{\beta 2}(N_{gt}),\ N_{\gamma 2} = 0,\ F_{\beta 2} = F_{\gamma 2} = X^-)$ given $s_1^r = (n = 2,\ N_{\beta 1}(N_{gt}),\ N_{\gamma 1} = 0,\ F_{\beta 1} = F_{\gamma 1} = X)$ is:

$$E\pi_2^r = (1-\lambda)^2(p_g X - 1) - 2c.$$

We can see:

$$\begin{aligned} E\pi_2^n - E\pi_2^r &= \lambda(p_b X - 1) + \lambda(1-\lambda)(p_g X - 1) + 2c \\ &> 0 \\ \text{iff } c &> -\frac{1}{2}[\lambda(p_b X - 1) + \lambda(1-\lambda)(p_g X - 1)] \end{aligned}$$

It is easy to check this condition is implied by Assumptions 1 and 2.[40]

[40] By Assumption 2, $c \geq \frac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$, we have

$$\begin{aligned} & \frac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g} - \{-\frac{1}{2}[\lambda(p_b X - 1) + \lambda(1-\lambda)(p_g X - 1)]\} \\ = \ & \frac{\lambda}{\lambda p_b + (1-\lambda)p_g}\{2(1-\lambda)(p_g - p_b) + \{[\lambda p_b + (1-\lambda)p_g]X - \lambda\}p_b \\ & -(1-\lambda)p_g + (1-\lambda)(p_g X - 1)[\lambda p_b + (1-\lambda)p_g]\} \\ \geq \ & \frac{\lambda}{\lambda p_b + (1-\lambda)p_g}\{(1-\lambda)(p_g - p_b) + (1-\lambda)(p_g X - 1)[\lambda p_b + (1-\lambda)p_g]\} \\ > \ & 0, \end{aligned}$$

where we use Assumption 1:
$[\lambda p_b + (1-\lambda)p_g]X > 1$.

Let $W_2^n(s)$ denote the expected payoff in a normal period when Bank 2 plays s_2. Given the other bank is playing the trigger strategy, Bank 2's expected discounted present value from playing s_2 is:

$$\begin{aligned} W_i^n(s_2) &= E\pi_2^n + \delta(1-q)W_i^n(s_2) \\ &\quad +\delta q[\sum_{t=1}^{T} \delta^{t-1} E\pi_2^r + \delta^T W_i^n(s_2)]. \end{aligned}$$

We have:

$$\begin{aligned} W_i^n(s_2) &= \frac{E\pi_2^n + \delta q \frac{1-\delta^T}{1-\delta} E\pi_2^r}{1-\delta(1-q)-\delta^{T+1}q} \\ &= \frac{E\pi_2^n + q\frac{\delta-\delta^{T+1}}{1-\delta} E\pi_2^r}{1-\delta+(\delta-\delta^{T+1})q} \\ &= \frac{E\pi_2^n - E\pi_2^r}{1-\delta+(\delta-\delta^{T+1})q} + \frac{E\pi_2^r}{1-\delta}. \end{aligned}$$

In the normal period, Bank 2 can deviate from the equilibrium strategy by playing s_2' as defined earlier. The short-run payoff to Bank 2 is:

$$E\pi_2' = (1-\lambda)(p_g X - 1) + \lambda[(1-\lambda)(p_g X - 1) + \lambda(p_b X - 1)] - c$$

and we have the expected one-shot deviation discounted present value of Bank i:

$$\begin{aligned} W_i^n(s_2') &= E\pi_2' + \delta(1-q')W_i^n(s_2) \\ &\quad +\delta q'[\sum_{t=1}^{T} \delta^{t-1} E\pi_2^r + \delta^T W_i^n(s_2)] \end{aligned}$$

In order to make the trigger strategy the best response to each other in normal periods, we need:

$$W_i^n(s_2) > W_i^n(s_2').$$

It is easily verified that there is no incentive for either bank to deviate in a reversionary period as long as δ is close enough to 1 and T is large enough.

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