Bank Credit Cycles*

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Abstract

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

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1 Introduction

In this paper we show that periodic credit crunches, swings between high and low credit allocations, are an inherent part of banking due to the way banks compete for borrowers. 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. 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. Extensive empirical tests of the model are presented, based on parameterizing the public information that is the basis for banks' beliefs about rivals' strategies. These information measures concern rival banks' relative performance, encapsulated in a Performance Difference Index (PDI). The empirical behavior of U.S. bank credit card lending, commercial and industrial lending, and bank profitability, are consistent with the model. Bank credit cycles are a systematic risk. We find that, consistent with this, the PDI is a priced factor in an asset pricing model of bank stock returns. Most importantly, the PDI is a priced factor for non-financial firms as well, and increasingly so as firm size declines.

Changes in bank credit allocation, sometimes called "credit crunches," appear to be an important part of macroeconomic dynamics. Bank lending is procyclical.[1] Rather than change the price of loans, the interest rate, banks sometimes ration credit.[2] A dramatic example in the U.S. is the period shortly after the Basel 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.[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.[4] The most direct evidence

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

[2] 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).

[3] See Keeton (1994) and Furfine (2001). This episode is the focus of the empirical literature on credit crunches. 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] In the absence of detailed information about banks' internal workings, it is not exactly clear what is meant by the term "lending standards." It can refer to all the elements that go into making a credit decision, including credit scoring models, the lending culture, the number of loan officers and their seniortiy and experience, the banks' heirarchy of decision-making, and so on.

comes from the Federal Reserve System's Senior Loan Officer Opinion Survey on Bank Lending Practices.[5] Banks are asked whether their "credit standards" for approving loans (excluding merger and acquisition-related loans) have "tightened considerably, tightened somewhat, remained basically unchanged, eased somewhat, or eased considerably." Lown and Morgan (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), and they conclude that cycles in bank lending standards are important in explaining aggregate economic activity.

In a macroeconomic context changes in the Fed Lending Standards Index (the percentage of respondents reporting tightening) Granger-causes changes in output, loans, and the federal funds rate, but the macroeconomic variables are *not* successful in explaining variation in the lending standards index. The Lending Standards Index is exogenous with respect to the other variables in the Vector Autoregression system. See Lown and Morgan (2001, 2002) and Lown, Morgan and Rohatgi (2000).[6] The analysis in this paper is aimed at explaining the forces that cause lending standards to change and, in particular, to explaining how this can happen independently of macroeconomic variables.

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] We study a model of bank competition in which banks collude to set high loan rates (hence loan rates are sticky), and they implicitly agree not to (over-) invest in costly information production about prospective borrowers.[8] A bank can strategically produce more information than its rivals and then select the better borrowers, leaving unknowing rivals with adversely selected loan

[5] 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/>.

[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 in a dynamic way.

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

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

Empirically testing models of repeated strategic interaction of firms has focused on price wars. See Reiss and Wolak (2003) and Bresnahan (1989) for surveys of the literature. However, our model predicts there are "information production wars." Since information production is unobservable, we can not follow the usual empirical strategy. We propose a new method for testing the model, which we believe to be of independent interest. Our approach tests a general implication of any equilibrium of the model with imperfect competition by identifying the relevant public information and its relation with "information production wars"–credit crunches. In theory, to detect deviations by rivals, banks must look at two sources of public information: the number of loans made in a period by each rival and the default performance of each rivals' loan portfolio. We argue that the *relative* performance of *other* banks is the public information relevant for each bank's decisions about the choice of the level of information production. More importantly, the use of *relative* bank performance empirically distinguishes our theory from a general learning story, which would predict past bank performance matters for bank credit decisions.

Broadly, the empirical analysis is in three parts. First, we examine a narrow category of loans, U.S. credit card lending, where there are a small number of banks that appear to dominate the market. Since it is not clear which banks are rivals, we first analyze this lending market by examining banks pairwise. If the PDI increases, banks should reduce their lending and increase their information production resulting in fewer loan losses in the next quarter. We also examine bank profitability, using stock returns. Second, we analyze macroeconomic time series, including the Lending Standard Survey Index. We form an aggregate bank Performance Difference Index (PDI) based on the absolute value of the differences on all commercial and industrial loans of the largest 200 banks. 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 Fed's Lending Standard Survey responses (the percentage of banks reporting "tightening" their standards) in Lown and Morgan (2001). Thirdly, if credit crunches are endogenous, and a systematic risk, then they should be a priced factor in an asset pricing model of stock returns. Therefore, our final test is to ask whether the parameterization of banks' relevant histories is a priced risk factor in a four factor Fama-French asset pricing setting. We look at banks and nonfinancial firms by size, as credit crunches have larger effects on smaller firms. We find all the evidence to be consistent with the theory.

Other relevant work includes 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.[9] We test Rajan's idea in the empirical section. Two related theoretical models are provided by Dell'Ariccia and Marquez (2004) and Ruckes (2003). These papers show a link between lending standards and information asymmetry among banks, driven by exogenous changes in the macroeconomy. As distinct from these models, the fluctuation of banks' lending behavior in our paper is purely driven by the strategic interactions between banks instead of an exogenously changing economic environment.

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's implications 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. 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.[10] Each applicant can accept at most one loan offer, and if a loan is granted, the borrower invests in a one period project which will yield a return of $X < \infty$ if the project succeeds and returns 0 otherwise. A borrower whose project succeeds will use the return X to repay the loan, i.e., a borrower's realized cash flow is verifiable.

Banks are risk-neutral. They can raise funds at some interest rate, assumed to be zero. After receiving the loan applications, a bank can use a costly technology to produce information about the applicant's type. The credit worthiness testing results in determining the type of an applicant, but there is a per applicant cost of $c > 0$. Banks can test any proportion of their applicants. Let

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

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

n_i denote the number of applicants that are tested by bank i. We say that the more applicants that a bank tests, i.e., using the costly information production technology, the higher are its credit or lending standards.[11] 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. We assume that neither bank observes the other bank's credit standards, i.e., each bank is unaware of how many applicants the other bank tests. Results of the tests are the private information of the testing bank.

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

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

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

Each bank first chooses some (could be zero, could be all) applicants to test, then, depending on the test results, decides whether to make a loan offer for each applicant, and if yes, at what interest rate. We formally define the stage strategy of each bank in Appendix 1.

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 portfolio sizes and outcomes are publicly observable. Banks cannot communicate with each other.

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

2.1 Stage Nash Equilibrium

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

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

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

[11] 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.

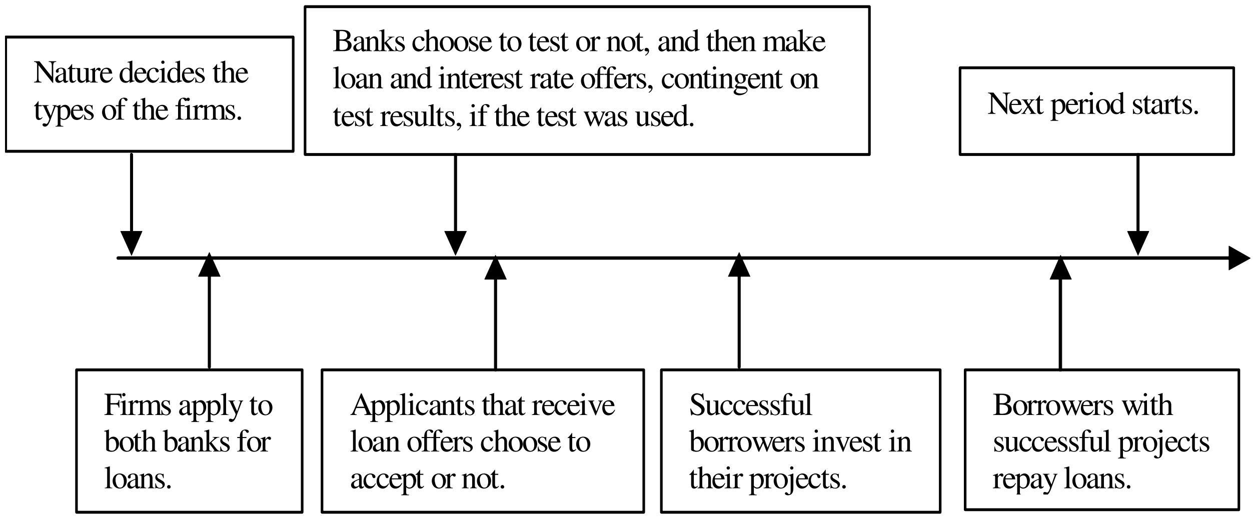

Figure 1: The Timing of the Stage Game

The proof is in Appendix 2.

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

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

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

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

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

The proof is in Appendix 2.[12] Intuitively, after the banks test some of the applicants, they will compete with each other for the good type applicants, which will drive the post-test profit to zero. However, since there is a test cost, ex-ante the banks' profits will be negative.

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

It is straightforward to characterize the optimal payoffs that the two banks receive in the stage game. If a bank does not conduct credit worthiness testing on an individual applicant and charges

[12] 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.

F, then the expected payoff from a loan to that individual applicant is:

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

which is maximized at $F = X$. If a bank conducts credit worthiness testing on an individual applicant and charges F, then the expected payoff from a loan to that individual applicant is:

$$\pi' = (1-\lambda)(p_g F - 1) - c,$$

which also is maximized at, say, $F = X$. It is easy to check that $\pi' < \pi$ with $F = X$ under Assumption 2.

3 Repeated Competition

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

By undercutting the interest rate offered to an applicant without credit worthiness testing, the expected payoff from this loan to the bank is:

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

Alternatively, the bank can test the applicant, undercut the interest rate if it is a good type, and undercut the interest rate to another untested applicant if the tested one turns out to be a bad type (this way the bank always gets one applicant for sure); the expected payoff to the bank is:

$$\pi' = \lambda[\lambda p_b F + (1-\lambda) p_g F - 1] + (1-\lambda)(p_g F - 1) - c.$$

We can show:

$$\pi' - \pi = \lambda(1-\lambda)(p_g - p_b)F - c,$$

which is increasing with F. Therefore, when F is high enough, banks will have incentive to produce information while manipulating the loan portfolio size through interest rates.

Formally, we consider sequential equilibria in which banks' strategies will depend on public information. In general, banks can base their strategies on all available information, both public and private. However, 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. 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). The available public information at the end of each period is the number of loans that each bank made (D_{it}) and the number of those loans that defaulted (χ_{it}).

We formalize the game in Appendix 1, and we restrict attention to symmetric PPE (SPPE) (defined below). Aside from seeing how the repeated game works, the main point is the demonstration that because banks have two actions that they can use to compete (i.e., changing lending rates and increasing information production), banks' beliefs must be based on the history of banks' portfolio sizes as well as banks' loan default performances.

3.1 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.[13] 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 perfect public equilibrium payoff for bank i can, as discussed in Appendix 1, be *factored* into a first-period stage payoff π_i (depending on the stage strategies of both banks) and a *continuation payoff function* u_i (depending on the public history). Let s_i be the stage strategy for bank i, 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. 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.

At a profitable interest rate, if a bank makes more loans than its rival, then 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

[13] 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.

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 the 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 3 *In any SPPE, in which neither bank tests any applicant and both banks make loan offers to all applicants at the same interest rate* F_α*, if* $c < \lambda(1-\lambda)(p_g - p_b)F_\alpha$*, then the continuation value functions cannot only depend on the number of loans made by each bank.*

The proof is in Appendix 2. 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 credit worthiness testing. The proposition says that banks' loan performances (i.e., number of defaults) matters in an SPPE with banks charging the same interest rate (high enough) to all the applicants and conducting no 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. The case with both banks offering loans to only a subset of the applicants without using the test is covered in the following corollary.

Corollary 1 *In any SPPE, in which neither bank tests any applicant and in which each bank makes loan offers to a subset* $2 \leq N_\alpha < N$ *of applicants at the same interest rate* F_α*, if* $c < \lambda(1-\lambda)(p_g - p_b)F_\alpha$*, then the continuation value functions cannot only depend on the number of loans made by each bank.*

The proof is in Appendix 2. The case with $N_\alpha = 1$ is covered by the next corollary.

Corollary 2 *In any SPPE, in which neither bank tests any applicant and in which each bank makes loan offers to a subset* $N_\alpha \leq N$ *of applicants at different interest rates, denoted by a vector* F_α*, if* $c < \frac{2N-1}{2N}\lambda(1-\lambda)(p_g - p_b)\min\{F_\alpha\}$*, then the continuation value functions cannot only depend on the number of loans made by each bank.*

The proof is in Appendix 2.

The conclusion is that when the banks want to avoid costly credit worthiness testing on the equilibrium path, then it is not possible for the two banks to collude on a high loan interest rate in a SPPE without looking at each other's loan performances. The possibility of deviating by using credit worthiness testing while manipulating the loan size, 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 over time.

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

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

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

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

The likelihood of default is higher:

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

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

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

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

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

We have:

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

Therefore, compared with punishing each other after a bad performance, doing that after a *relatively* bad performance incurs a smaller probability of a mistaken punishment ($q_r < q$), while it generates the same incentive to not to deviate ($\Delta q_r = \Delta q$). The measure of the "performance difference" excludes the case where both banks perform poorly, and excluding this case is empirically important because it can result from aggregate shocks, which we do not model.

In Appendix 3, 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.

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

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

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

The above discussions lead to our empirical tests in the next section: banks' relative performance are important for the credit cycles, which have significant impact on the economy.

4 Empirical Tests

The model proposes that banks form beliefs based on public information. The empirical strategy we adopt is to focus on one robust prediction that the theory puts forward, namely, that unlike a perfectly competitive lending market, in the imperfectly competitive lending market that we have described, public histories about rival banks should affect the decisions of any given bank. We construct measures of the relative performance histories of banks, variables that are at the root of beliefs and their formation. In particular, changes in beliefs about rival behavior should be a function of bank public performance differences.

In the U.S. the most important public information available about bank performance is the information collected by bank regulatory authorities (the Federal Reserve, Federal Deposit Insurance Corporation, and the Office of the Comptroller of Currency) in the quarterly Call Reports. While publicly-traded banks also file with the Securities and Exchange Commission, the Call Reports provide the detail on specific loan category amounts outstanding, charge-offs, and losses. We construct Performance Difference Indices based on the Call Reports that U.S. banks file quarterly with. These reports are filed by banks within 30 days after the last business day of the quarter, and become public roughly 25 to 30 days later.[14] For that reason, when we analyze the predictive

[14] Today banks submit their Call Reports electronically to Electronic Data Systems Corporation. It is then sent to the Federal Reserve Board and to the Federal Deposit Insurance Corporation, which subsequently release the data. This has of course changed over time. Nowadays, the information is available 25-30 days after it is filed on the web. Earlier private information providers would obtain computer tapes of the information from the National Technical

power of certain variables to be constructed based on the Call Reports, we use the one period lag when the contemporaneous variable is needed. Because the reports appear at a quarterly frequency, we analyze data at that frequency.

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

Another challenge for testing concerns identifying rival banks. 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 a function of geography or possibly bank size. These are empirical issues.

While the model suggests that there are two "regimes," normal times and punishment times, this is an artifact of simplifying the model. There could be a range of punishments, making the notion of a "regime" less discontinuous. This too is an empirical issue.

4.1 The Credit Card Loan Market

We first examine a specific, but important category of loans, credit card loans.[15] In the U.S. credit card lending market potential 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 Related Plans," as well as some other variables discussed

Information Service of the Department of Commerce. The information was then provided in published formats. We thank Mary West of the Federal Reserve Board for information on the timing of the reports.

[15] Despite the public availability of credit scores on individual consumers, banks retain important private information about credit card borrowers. Gross and Souleles (2002) show the additional explanatory power of private internal bank information in predicting consumer defaults on credit card accounts, using a sample where they were able to procure the private information.

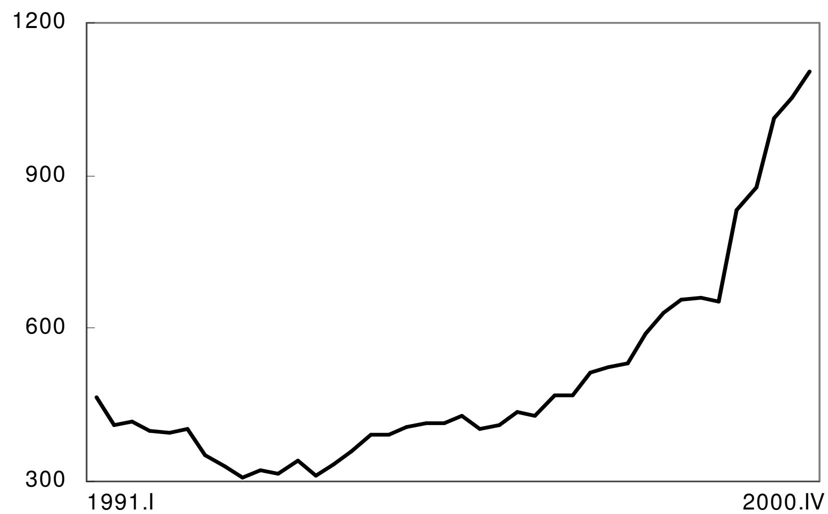

Figure 2: Herfindahl Index

below.[16]

The high concentration is shown by the Herfindahl Index for banks that are active in the credit card loan market pictured in Figure 2.[17] 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.

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 are measures of rival banks' relative histories that we hypothesize are the basis for each bank's beliefs about whether rivals have deviated. Our hypothesis is that these measures of bank histories will be significantly negative, even conditional on all the other variables.

In addition to collecting the quarterly bank holding company data 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),"

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

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

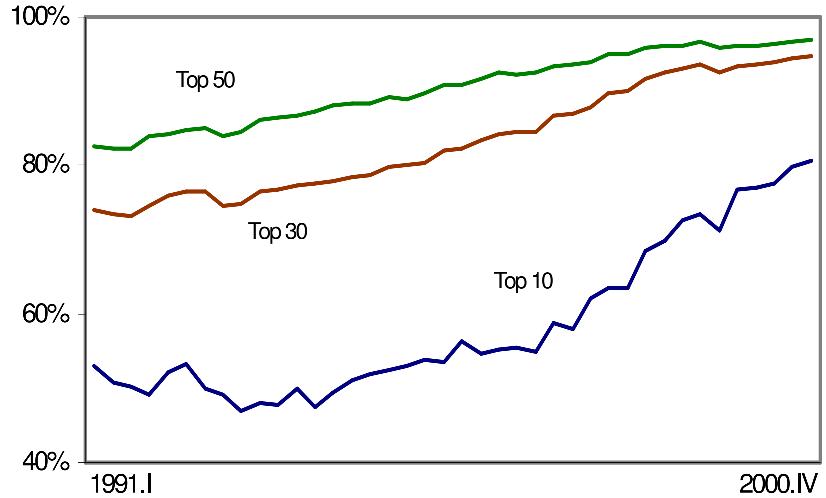

Figure 3: Shares of Top Bank Holding Companies in Credit Card Loan Market

"Recoveries on Loans to Individuals for Household, Family, and Other Personal Expenditures – Credit Cards and Related Plans (CRV)," and "Total Loans and Leases, Net (TLS)." We construct the following variables:

$$\text{Credit Card Loan Loss Rate } (CLL) = \frac{CCO - CRV}{CLS}$$
$$\text{Credit Card Loans to Total Loans Ratio } (CRL) = \frac{CLS}{TLS}.$$

Each variable is constructed for each bank holding company for each quarter.[18]

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)."[19]

4.1.2 Pairwise Tests of Rival Banks

We first look at banks pairwise. We do this for two reasons. First, it is not known which banks are rivals, and maybe not all banks are rivals. Second, we have only 40 quarterly observations for each bank, so examining several banks jointly quickly uses up the degrees of freedom. We focus on the

[18] We also collect data for "Total Assets ($ASSET$)," and costruct the variable: Credit Card Loans to Total Assets Ratio (CRA) = $\frac{CLS}{ASSET}$. The main regression results using CRA are similar to those using CRL. Thus we ommit the results for the sake of space.

[19] 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. Also, DPI is normalized by GDP.

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 America, Charlotte, NC (BOAM); Chase Manhattan Corp., New York, NY (CHAS); and Wachovia Corp.,Winston-Salem, NC (WACH).

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

$$y_{it} = \alpha_{ij} x_t + \beta_{ij} w_{it} + \gamma_{ij} z_{ijt} + \varepsilon_{it}, \text{ for } j \neq i \tag{1}$$

where

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

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. It is a particular parametrization of the relevant public information: the performance difference. This variable is lagged to be consistent with the fact the Call Report information is publicly available with a lag. For the current quarter, the most recent public information would be about last quarter. Conditional on the state of the macroeconomy and bank holding company i's own past performance, we ask whether bank holding company i's lending decisions depend on the observed absolute value of the differences between it's own past performance and that of its rival, bank holding company j. For each measure of the relative difference in loan performance, we test whether $\gamma = 0$, using a Wald test (chi-squared distribution). The results are shown in Table 1.[20]

In Table 1, 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 by '#.' Most coefficients are negative, which matches the theoretical prediction. When the difference between the loan performance history is large, it leads to (an increase in lending standards and, consequently) a subsequent decrease in (lower quality) loans

[20] The result in entry (i, j) in the table comes from the regression of bank i's loan loss ratio (or asset allocation) as the dependent variable.

CLL	CITI	BONE	MBNA	BOAM	CHAS	WACH
CITI	−−	-0.1896 (0.104)*	-0.3115 (0.068)*	0.1160 (0.726)	-0.0597 (0.983)	-0.2686 (0.001)**
BONE	-0.3339 (0.001)***	−−	-0.4543 (0.000)***	-0.3385 (0.239)	-0.4876 (0.066)*	-0.2546 (0.199)
MBNA	-0.0025 (0.910)	-0.0114 (0.800)	−−	0.0089 (0.676)	0.0790 (0.087)#	-0.0724 (0.375)
BOAM	-0.1310 (0.929)	-0.1666 (0.381)	-0.3834 (0.000)***	−−	0.4371 (0.000)###	-0.4024 (0.451)
CHAS	-0.1328 (0.777)	-0.0170 (0.869)	0.0603 (0.481)	0.0784 (0.221)	−−	-0.1906 (0.590)
WACH	-0.1278 (0.000)***	-0.0809 (0.312)	-0.2117 (0.006)***	0.0236 (0.947)	-0.0198 (0.018)**	−−

CRL	CITI	BONE	MBNA	BOAM	CHAS	WACH
CITI	−−	-0.4807 (0.004)***	0.1403 (0.671)	-0.2671 (0.093)*	1.2131 (0.087)#	-0.5353 (0.000)***
BONE	-1.2008 (0.000)***	−−	-2.4739 (0.000)***	-1.6719 (0.0609)*	-1.4095 (0.518)	-1.9717 (0.029)**
MBNA	0.2569 (0.839)	0.8216 (0.049)##	−−	-0.6914 (0.3577)	-0.5540 (0.413)	1.1749 (0.000)###
BOAM	-0.2932 (0.000)***	-0.2859 (0.027)**	-0.2608 (0.254)	−−	0.2274 (0.013)##	-0.2283 (0.550)
CHAS	-0.2586 (0.903)	-0.1209 (0.227)	-0.1075 (0.981)	-0.1433 (0.6790)	−−	-0.4296 (-0.077)*
WACH	-0.3865 (0.010)***	-0.8394 (0.000)***	-0.6496 (0.006)***	0.0345 (0.8199)	0.7314 (0.091)#	−−

Table 1: Results for Pairwise Regressions

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 a problem that we do not know how many significant chi-squared statistics would be expected to be significant in a small sample. We address this issue using a bootstrap (see Horowitz (2001) for a survey). We bootstrap to test if the results in Table 1 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 SI^* (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.[21] 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 $y_{it} = CLL_{it}$ or CRL_{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.

[21] Admittedly there is some arbitrariness in how the Significance Index is constructed. However, we tried constructing the Signficance Index in a number of ways, and found that the results are robust.

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

Table 2: Bootstrap Results

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

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. $\Pr(SI \geq SI^*)$.

The results are reported in Table 2. The sample Significance Indices are: $SI^*_{CLL} = 34$ and $SI^*_{CRL} = 36$. The p-values are presented in Table 2.

We conclude that the Null hypothesis is rejected.

4.1.3 Threshold Effects

A literal interpretation of the model would mean that there are two "regimes," rather than a possible large number of levels of intensity of information production. Perhaps there is a threshold effect, in that only if the absolute performance differences reach a certain critical level does (mutual) punishment occur. We investigate this by specifying a different measure of the absolute difference as shown in the model below. For each bank i, define $y^1_{it} = CLL_{it}$, and $y^2_{it} = CRL_{it}$, and write the model specification as follows:

$$\begin{aligned} y^k_{it} &= \alpha^k_{ij}x_{it} + \beta^k_{ij}w_{it} + \gamma^k_{ij}z_{ijt} + \varepsilon^k_{ijt},\ \varepsilon^k_{ijt} \sim N(0, \sigma^k_{ij}) \ \text{ for } j \neq i, \\ \text{and } z_{ijt} &= \max\{0, |CLL_{it} - CLL_{jt}| - TH_{ij}\}. \end{aligned}$$

The new z_{ijt} measures the value of performance difference, measured by $|CLL_{it} - CLL_{jt}|$, in excess of certain threshold, TH_{ij}, which does not change over time or across k, and which is to be estimated. For each pair of banks, (i, j), we estimate the parameters using maximum likelihood:

$$\{\widehat{\alpha^k_{ij}}, \widehat{\beta^k_{ij}}, \widehat{\gamma^k_{ij}}, \widehat{TH_{ij}}, \widehat{\sigma^k_{ij}}\} = \max_{\alpha^k_{ij}, \beta^k_{ij}, \gamma^k_{ij}, TH_{ij}, \sigma^k_{ij}} \sum_k \sum_t [-\ln \sigma^k_{ij} - \frac{(y^k_{it} - \alpha^k_{ij}x_{it} + \beta^k_{ij}w_{it} + \gamma^k_{ij}z_{ijt})^2}{2(\sigma^k_{ij})^2}].$$

We proceed as above by for each pair of banks (omitted here) and then bootstrapping. The final p-value results are shown in Table 3.

The threshold effects are significant with the newly constructed beliefs variables, z_{ijt}, though the results are not uniformly different than those using the absolute difference variables directly.

	p-value
SI_{CLL}	0.0096
SI_{CRL}	0.0018

Table 3: Bootstrap Results for Threshold Effects

	p-value
SI_{CLL}	0.0138
SI_{CRL}	0.0024

Table 4: Boostrap Results in the Presence of Learning Effects

4.1.4 Learning as an Alternative Hypothesis

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 (1), we replace w_{it} with w_{ijt}:

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

The tables showing the estimated coefficient on the absolute performance difference coefficients are omitted for the sake of space. The main results are similar to Table 1. The same pattern of competition between Citicorp, Bank One, and Wachovia appears, as in Table 1. 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 y_{it}, x_t and w_{it} defined in 2.

The sample Significant Indices are: $SI^*_{CLL} = 36$ and $SI^*_{CRL} = 28$. The p-values are presented in Table 4.

The information contained in the absolute difference variables remain significant, in the presence of the most general specification of learning.

4.1.5 An Aggregate Performance Difference Index

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

	$y_{it} = CLL_{it}$	$y_{it} = CRL_{it}$
CITI	-0.7895 (0.2927)	-2.1500 (0.0073)***
BONE	-1.5211 (0.1038)*	-6.1892 (0.0003)***
MBNA	0.0631 (0.6693)	1.3084 (0.3235)
BOAM	-0.5212 (0.0354)**	-0.5189 (0.0050)***
CHAS	-0.3860 (0.0873)*	-0.0521 (0.3381)
WACH	-0.4333 (0.0003)***	-1.4574 (0.0330)**

Table 5: Results for the Performance Difference Index

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

This Performance Difference Index measures the average difference of the competing banks' loan performances.[22] (The denominator comes from having six banks, leading to fifteen different pairs in total.) 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} defined in 2, and $z_{it} = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$. The results are reported in Table 5.

Table 5 presents the average value of the coefficients of z_{ij} and the p-value (in parentheses) of the Wald test ($\chi^2(4)$). Table 5 shows that, aside from MBNA, all the banks have negative and significant coefficients for PDI, confirming the conjecture from the theory. When there is a large performance difference across all the rival banks, banks raise their lending standards to punish each other, and consequently future loan losses go down. The standard deviation of PDI is 0.00444, the average coefficients on PDI for CLL and CRL are -0.598 and -1.510, and the mean of CLL and CRL are 0.0246 and 0.242. When PDI changes by one standard deviation, CLL decreases by 0.00266 (10% of the mean), and CRL decreases by 0.00671 (3% of the mean). Therefore, the effects of PDI are also economically important.

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

4.1.6 Rajan's Reputation Hypothesis

Rajan (1994) argues that reputation considerations of bank managers cause banks to simultaneously raise their lending standards when there is an aggregate shock to the economy causing the loan performance of all banks to deteriorate. Banks tend to neglect their own loan performance history in order to herd or pool with other banks. Rajan's empirical work focuses on seven New England banks over the period 1986-1991. His main finding is that a bank's loan charge-offs-to-assets ratio is significantly related not only to its own loan loss provisions-to-total assets ratio, but also to the average charge-offs-to-assets ratio for other banks (instrumented for by the previous quarter's charge-offs-to-assets ratio).

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.[23] 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:

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

where with y_{it}, x_t and w_{it} defined in 2, and $z_t = AGLL_{t-1}$.

The coefficients on $AGLL_{t-1}$ and the associated p-values of t-statistics are reported in Table 6.[24]

Rajan's (1994) hypothesis 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, the coefficients of the aggregate loan loss rate are all positive, with a few exceptions. If we remove the other macroeconomic variables from the regression, i.e. $x_t = (C, T, S_1, S_2, S_3)$, the results are basically the same.

4.1.7 Bank Stock Returns and Performance Differences

In a credit crunch banks make fewer loans and spend more on information production, so their profitability declines. In this section, we test that implication of the model. Specifically, we ask whether the Performance Difference Index has predictive power for the stock returns of each top bank holding company in credit card loans. We collect the stock return from CRSP from 1991.I to 2000.IV. During this period, Citicorp, Bank of America, and Chase Manhattan are involved in mergers.[25] We carry out the tests for all six bank holding companies and for the three bank

[23] 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.

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

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

	$y_{it} = CLL_{it}$	$y_{it} = CRL_{it}$
CITI	0.6620 (0.0167)	1.6366 (0.0108)
BONE	1.3343 (0.0049)	4.3686 (0.0020)
MBNA	0.0726 (0.3395)	-1.9956 (0.0028)**
BOAM	0.4734 (0.3306)	0.3611 (0.3016)
CHAS	0.0597 (0.7445)	-0.5579 (0.3238)
WACH	0.3151 (0.1974)	1.7023 (0.0126)

Table 6: Test of the Reputation Hypothesis

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 cut lending. Consequently, their profit margins will be lower. Therefore, we expect to see negative loadings on the lags of the PDI. Note that this is not an asset pricing model, but a test concerning bank profits, as measured by stock returns. The regression equations are:

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

We use Seemingly Unrelated Regression to estimate the system of equations, with the restriction that the β_is be the same across banks (we allow for different intercepts).[26]

Table 7 shows the Seemingly Unrelated Regression results about the predictive power (on stock returns) of the PDI for the two cases: six and three bank holding companies. From Table 7, we see that the PDI from the previous year significantly predicts the stock return for the current period. For the case with six banks, the Wald test of the hypothesis that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ gives $\chi^2 = 20.6229$, with p-value 0.0004. For the case with three banks, the Wald test of the hypothesis that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ gives: $\chi^2 = 10.2850$, with p-value 0.0359. Therefore, the PDI that we constructed does have predictive power for the stock return. Even though we are only looking at credit cards, keep in mind that these six banks dominate this market, so their profits are significantly affected by this sector.[27]

[26] In the regressions, we take out the mean and the seasonal effects from the Performance Difference Index (PDI).

[27] Since the dividend yield is well known to be a predictor of future stock returns (see, e.g., Cochrane (1999)), we also include dividend yields in the regressions (using the dividends of each bank from CRSP). The results on the predictive power of PDI are unchanged with the inclusion of the dividend yield. These results are omitted for the sake of space.

Six Banks	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)***		
	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)

Three Banks	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)***
	α_2	α_3	α_6	
coeff. ($t-stat$)	0.0248 (1.0519)	0.0944 (3.7058)	0.0297 (2.1434)	

Table 7: Results for Stock Return Prediction Using Seemingly Unrelated Regressions

4.2 VAR Analysis of the Fed's Lending Standards Index

In this section we extend the empirical analysis in two important ways. First, we go beyond credit card lending at six banks to examine commercial and industrial loan market at an aggregate level. Second, we probe the implications of the theory for macroeconomic dynamics.

If banks increase their information production, that is, they 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 system of equations lets us control for the feedback between current and past levels of performance differences, the lending standard survey results, and macroeconomic variables. Given estimates of these interactions, we can identify the impact that unpredictable shocks in performance difference public histories have on other variables in the system. We first ask whether the performance difference histories 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) in analyzing the time series of survey responses, the percentage of banks reporting tightening in the survey. 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

	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 8: Results for VAR Analysis

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:[28]

$$PDI = \frac{\sum_{i>j} |LAR_i - LAR_j|}{19,900}.$$

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.[29]

As before, we conjecture that this PDI captures the relevant history that is at the basis of banks' beliefs about whether other banks are deviating to using the credit worthiness tests.[30]

4.2.1 VAR Results

The VAR includes four lags of the four endogenous variables: bank lending standards ($STAND$) (i.e., the percentage of survey respondents reporting tightening), the Performance Difference Index (PDI), the federal funds rates (FFR), and the log of commercial bank loans ($LOGLOAN$). Bank lending standards are a loan supply side factor and the federal funds rate affects loan demand; commercial bank loans are the equilibrium outcomes. The PDI is hypothesized to capture banks' 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.

Table 8 presents the average value of the coefficients and p-values (in parenthesis) of the Wald test ($\chi^2(4)$) of the VAR with four lags of the lending standards, the PDI, log commercial bank loans, and federal funds rate. Table 8 shows that the PDI Granger-causes all the other three endogenous

[28] Some banks report the loan loss or loan allowance semi-annually instead of quarterly, so we drop these zero values in the calculation below. Therefore, the denominator is not necessarily 19,900.

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

[30] We also constructed a PDI using loan charge-off ratios. The empirical results are similar and are omitted to save space.

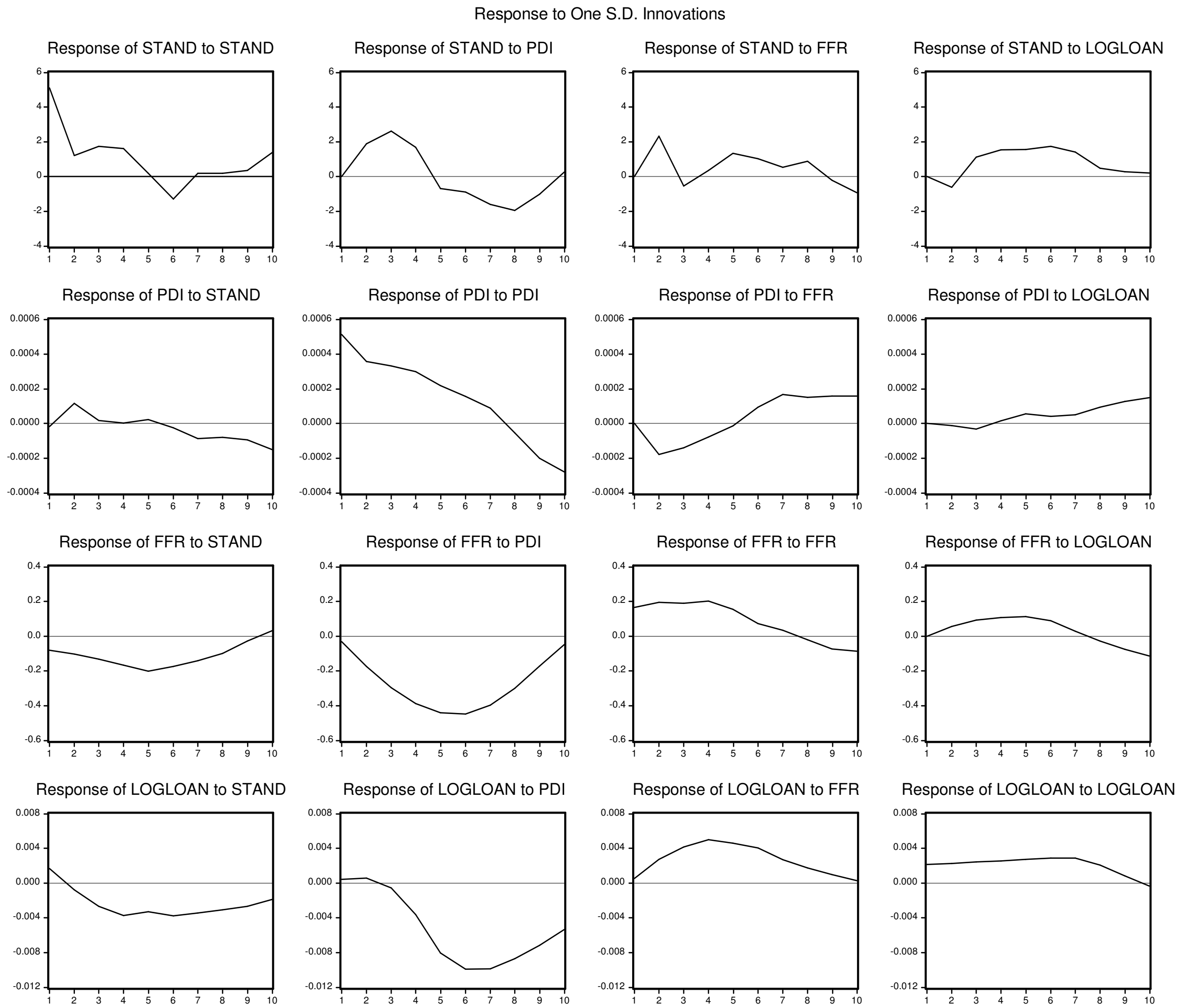

Figure 4: Impulse Responses in the Macroeconomy

variables, but not vice versa. An increase in PDI immediately causes a rise in $STAND$, 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 observe this pattern in the graph of impulse responses in Figure 4.[31]

[31] The ordering of the variables in a VAR matters for the impulse response functions since the Cholesky decompositions of the variance-covariance matrix are different with different orderings (see Hamilton (1994) for more details). Placing PDI as the second variable in the VAR is a relatively conservative way (in comparison with placing it as the first one) of displaying the effects of PDI.

4.3 Asset Pricing and Credit Crunches

Strategic competition between banks results in periodic credit crunches, a systematic risk. Consequently, if the stock market is efficient, then the stock returns of both banks and non-financial firms, which, at least partially, rely on banks for external financing, should reflect the competition between banks. In this section we turn to a different empirical approach, namely, we look for the hypothesized systematic effects in an asset pricing context. If strategic behavior between banks causes credit cycles, then it causes variation in the profitability of non-financial firms, which are affected by credit crunches. At the same time, credit crunches are not profitable for banks. The credit cycle is a systematic risk, and therefore should be a priced factor in stock returns, to the extent that this factor is not already spanned by other factors. We conjecture that the constructed PDI should be a priced risk factor for both banks and non-financial firms. That is, in the context of an asset pricing model of stock returns, there should be an additional factor, namely, the Performance Difference Index. Moreover, since relatively smaller firms are more dependent on bank loans (see, e.g., Hancock and Wilcox (1998)), we expect that the coefficients on PDI are larger for smaller firms.

We adopt the widely-used Fama-French three factor empirical asset pricing model, augmented with a momentum factor (as has become common practice).[32] The models says that the sensitivity of a firm's expected stock return depends on four factors: the excess return on a broad based market portfolio, $r_m - r_f$; the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (small minus large), SMB; the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (high minus low), HML; the momentum factor, MOM, is the difference between the return on a portfolio of past winners and the return on a portfolio of past losers. To this we add last quarter's PDI; the model is estimated using quarterly data, as PDI can only be calculated quarterly.[33]

We hypothesize that bank stock returns will be sensitive to PDI and that PDI is not spanned by the other factors. Further, non-financial firms' stock returns will also be sensitive, increasingly so for smaller firms. The monthly firm returns are collected from CRSP (then transformed into quarterly data). We separate out commercial banks and non-financial firms based on their SIC codes, and then divide the non-financial firms into ten deciles based on the capitalizations. The data cover the period 1976.I to 2001.IV.

Table 9 reports the coefficients and t-statistics of the four factor regression with $r_m - r_f$, SMB, HML, MOM and PDI as the risk factors. The results in Table 9 show that the Performance Difference Index (PDI) is a significant risk factor for both banks and all non-financial firms with

[32] See Fama and French (1993, 1996). Carhart (1997) introduced an additional factor, the momentum factor. We collect the quarterly Fama-French three factors and monthly momentum factor (then transformed into quarterly data) from French website (the construction method can also be found there). The risk free rates are three-month T-Bill rates from FRED II (we use the rate of the first month in each quarter) at Federal Reserve Bank at St. Louis.

[33] We use the lag of PDI since there is a lag in the Call Reports becoming publicly available, as we discussed earlier. We take out the mean from PDI, which does not affect the estimation of β.

	α	$r_m - r_f$	SMB	HML	MOM	PDI	R^2
	Commercial Banks						
β	-3.482	0.961	0.088	-0.092	0.011	360.7	0.924
(t-stat)	(-11.07)***	(23.72)***	(1.69)*	(-1.81)*	(0.25)	(4.63)***	
	Non-Financial Firms						
Dec1	-13.32	0.506	1.547	0.137	0.126	876.0	0.587
(small)	(-11.25)***	(3.32)***	(7.88)***	(0.71)	(0.72)	(2.99)***	
Dec2	-8.18	0.716	1.650	0.108	0.117	836.6	0.752
	(-8.68)***	(5.90)***	(10.55)***	(0.71)	(0.85)	(3.59)***	
Dec3	-6.159	0.870	1.729	0.177	0.160	835.4	0.825
	(-7.45)***	(8.18)***	(12.61)***	(1.32)	(1.32)	(4.09)***	
Dec4	-4.933	0.856	1.599	0.026	0.103	753.1	0.870
	(-7.29)***	(9.83)***	(14.25)***	(0.23)	(1.04)	(4.50)***	
Dec5	-4.00	0.924	1.536	0.016	0.081	698.85	0.909
	(-7.13)***	(12.80)***	(16.52)***	(0.17)	(0.99)	(5.04)***	
Dec6	-3.093	0.993	1.373	-0.109	-0.061	540.4	0.947
	(-7.35)***	(18.32)***	(19.66)***	(-1.59)	(-0.99)	(5.19)***	
Dec7	-2.110	1.007	1.205	-0.152	-0.093	421.0	0.946
	(-5.17)***	(19.18)***	(17.81)***	(-2.30)**	(-1.55)	(4.17)***	
Dec8	-1.864	1.039	0.919	-0.164	-0.092	438.7	0.935
	(-4.45)***	(19.27)***	(13.22)***	(-2.41)**	(-1.50)	(4.23)***	
Dec9	-1.945	0.974	0.598	-0.150	-0.071	450.3	0.906
	(-4.44)***	(17.28)***	(8.23)***	(-2.12)**	(-1.10)	(4.15)***	
Dec10	-2.239	0.889	-0.059	-0.264	-0.051	383.7	0.893
(large)	(-6.04)***	(18.64)***	(-0.96)	(-4.39)***	(-0.94)	(4.19)***	

Table 9: Results for Risk-Factor Analysis

different sizes. Note that the coefficients on PDI for smaller firms are larger, thus confirming our conjectures. The standard deviation of PDI is 0.00133. Therefore, when PDI changes by one standard deviation, the excess return for banks and large non-financial firms changes by about 50 basis points, while the excess return for small non-financial firms changes by about 100 basis points. We conclude that the competition and collusion among banks is an important risk factor for stock returns. The size effect further demonstrates that the Performance Difference Index we constructed is not capturing some sort of learning effect about macroeconomic condition, which would be spanned by the other risk factors, or at least would have been priced approximately equally for both large firms and small firms (as $r_m - r_f$ is).

5 Conclusion

An important message of Green and Porter (1984) is that collusion can be very subtle. The subsequent empirical work focused on price wars as possible dramatic examples of such imperfect competition. We studied banking, an industry in which there have not been price wars. Banking is an industry with limited entry; it is a highly concentrated industry, and it is an industry that is informationally opaque and hence regulated. The information opaqueness affects competition for borrowers in that rivals can produce information with different precision. This causes the imperfect competition in banking to take a different form from other industries. In particular, we showed that the intertemporal incentive constraints implementing the collusive arrangement (of high interest rates and low cost information production) required periodic credit crunches.

Our empirical approach to testing proceeds at the level of the public information that 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.

Appendix 1: The Formal Game

Formalization of the Stage Strategy

Bank i randomly chooses n_i applicants to test. For those applicants that bank i does not test, it will decide to approve applications to $N_{\alpha i} \leq N - n_i$ 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. 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 $F_{\beta i}$. 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. In general, $F_{\alpha i}$, $F_{\beta i}$ and $F_{\gamma i}$ could vary among the corresponding category of applicants, i.e., different applicants in the same category could possibly get offers of loans at different interest rates. Therefore, we interpret $F_{\alpha i}$, $F_{\beta i}$ and $F_{\gamma i}$ as vectors of interest rates charged to those approved non-tested applicants.

The stage strategy of a bank is:

$$s_i = \{n_i, N_\alpha(n_i, N_{gi}), N_\beta(n_i, N_{gi}), N_{\gamma i}(n_i, N_{gi}), F_{\alpha i}(n_i, N_{gi}), F_{\beta i}(n_i, N_{gi}), F_{\gamma i}(n_i, N_{gi})\}, \quad (3)$$

where:

n_i : the number of applicants that bank i tests;

N_{gi} : the number of good applicants found by bank i with the test;

$N_{\alpha i}$: the number of applicants that bank i offers loans to without test;

$N_{\beta i}$: the number of applicants that pass the test and get a loan from bank i;

$N_{\gamma i}$: the number of applicants that fail the test and get a loan from bank i;

$F_{\alpha i}$: the interest rate on the loan that bank i offers to the applicants without a test;

$F_{\beta i}$: the interest rate on the loan that bank i offers to the applicants that pass the test;

$F_{\gamma i}$: the interest rate on the loan that bank i offers to the applicants that fail the test.

Formalization of the Repeated Game

Assume that the two banks play the lending market stage game period after period, each with the objective of maximizing its expected discounted stream of profits. Upon entering a period of play, a bank observes only the history of:

(i) its own use of the credit worthiness test and the results;

(ii) its own interest rate on the loan offered to applicants;

(iii) its own choice of applicants that it lent to;

(iv) its own and its competitor's loan portfolio size (number of loans made);

(v) its own and its competitor's number of successful loans.

For bank i, a full path play is an infinite sequence of stage strategies as in (3). 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 ($\alpha \equiv$untested, approved, applicants; $\beta \equiv$tested, good types, approved; $\gamma \equiv$tested, bad types, approved). Define:

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

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

At the beginning of period T bank i has an information set: $h_i^{T-1} = \{a_{it}, K_{it}, \kappa_t\}_{t=0}^{T-1} \in H_i^{T-1}$, 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 bank i (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}: $H_i^{T-1} \rightarrow S$, 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}: $H^{T-1} \rightarrow S$.

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 outcomes ($\{\kappa_{it}\}_{t=0}^{\infty}, i = 1, 2$). 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

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

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.[34] 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 stage 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, for a game with N players, 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. Denote $\mathcal{N}$ as the set of non-negative integers, and 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:

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

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.[35]

Lemma 1 *The operator T maps compact sets to compact sets.*

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

[35] 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"

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.

determine the continuation values. This convexifies the set of equilibrium continuation values. This is a standard assumption. E.g., see Cronshaw and Luenberger (1994).

Appendix 2: Proofs

Proof of Proposition 1

We first prove the following lemma.

Lemma 2 *If it exists, in any symmetric stage Nash equilibrium in which neither bank conducts credit worthiness testing, each bank offers loans to all the loan applicants at the same interest rate.*

Proof. It is easy to check that if bank i is playing $s_i = (n_i = 0, N_{\alpha i} < N, F_{\alpha i})$, then bank $-i$ can strictly increase its profits by playing $s'_{-i} = (n_{-i} = 0, N'_{\alpha -i} = N, F'_{\alpha -i})$, where the strategy s'_{-i} is to offer $F'_{\alpha -i} = F_{\alpha i}$ to $N_{\alpha i}$ applicants (although these $N_{\alpha i}$ applicants might not be the same applicants that bank i is offering loans to), and offer X to the rest of them.

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

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

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 2, 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 conduct credit worthiness testing on at least one loan applicant and to offer loans to those applicants that pass the test, offering an interest rate F^{*-}, which is lower than F^* by an infinitely small amount. To see this consider a bank that deviates by conducting credit worthiness testing on one applicant. The expected profit from this deviation is:

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

We have:

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

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

Proof of Proposition 2

We first prove the following three lemmas.

Lemma 3 *In any symmetric stage Nash equilibrium in which both banks test all the applicants, each bank offers loans to all the applicants that pass the test at the same interest rate.*

The proof is similar to Lemma 2 and is omitted.

Lemma 4 *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 $F^{**} = \frac{1}{p_g}$.*

The proof is similar to Lemma 2 and is omitted.

Lemma 5 *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 2, we conclude that each bank offers loans to all non-tested applicants at the same interest rate.

If there does not exist a feasible F such that the banks can make a non-negative profit by lending to non-tested applicants at F, we conclude that each bank offers loans to none of those non-tested applicants.[36] ■

Proof. (Proposition 2) The proof is by contradiction. If in equilibrium both banks conducting credit worthiness testing on all the applicants, from Lemmas 3, 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. 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:

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

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:

[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 exist an F such that the banks can earn strictly positive profit by offering loans to a non-tested applicant. In this case, each bank can possibly offer to a subset of the non-tested applicants. However, including this case will not affect the results in Proposition 2.

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

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

Proof of Proposition 3

Proof. (Proposition 3) 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 $0 \le D \le N$, we must have:

$$E[\pi_1(s'(D), s) + \delta u_1(D, N-D)] = E[\pi_1(s'(D'), s) + \delta u_1(D', N-D')],\ \text{for any } D \ne D'.$$

[37]

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

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

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) another untested applicant. 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 $c < \lambda(1-\lambda)(p_g - p_b)F_\alpha$.[38]

[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.

[38] Recall Assumption 2: $c \ge \frac{(1-\lambda)\lambda(p_g - p_b)}{\lambda p_b + (1-\lambda)p_g}$. 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 of Corollary 1

Proof. (Corollary 1) The proof is similar to that of Proposition 3. 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.

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:

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

which implies:

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

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 $N_\alpha = N - 1$ is similar, thus omitted. ■

Proof of Corollary 2

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:

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

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

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

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 3: 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 $(1, 1)$.[39] 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:

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

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

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.

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 $(0,0)$,[40] then they will play (s^d, s^d) for the rest of

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

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

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 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

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

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.[41]

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:

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

[41] 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:
$[\lambda p_b + (1-\lambda)p_g]X > 1.$

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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