

# Bank Credit Cycles

G. B. GORTON

*The Wharton School University of Pennsylvania and NBER*

and

PING HE

*School of Economics & Management, Tsinghua University*

*First version received September 2005; final version accepted December 2007 (Eds.)*

A bank determines whether potential borrowers are creditworthy, that is, whether they meet the bank's credit or lending standards. In making this determination, each bank is in competition with other banks, but without knowing the competitor banks' credit standards. The resulting unique form of competition leads to endogenous credit cycles, periodic "credit crunches". Empirical tests of this repeated bank lending game are constructed based on parameterizing public information about relative bank performance that is at the root of banks' beliefs about rival banks' lending standards. 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, the relative bank performance of commercial and industrial loans is an autonomous source of macroeconomic fluctuations. In an asset pricing context, the relative bank performance is a priced risk factor for both banks and non-financial firms. The factor coefficients for non-financial firms are decreasing with size, consistent with smaller firms being more bank dependent.

## 1. INTRODUCTION

The essence of banking is the determination as to whether a potential borrower is creditworthy, that is, whether the potential borrower meets the bank's credit standards. When each bank makes this determination, it does so in competition with other banks, each with its own proprietary lending standards. In this paper we analyse this bank competition, presenting a repeated game of bank lending, in the style of Green and Porter (1984), in which banks can change their lending standards. In the theoretical model, we show that the bank competition for borrowers leads to periodic credit crunches, swings between high and low credit allocations. The reason is that bank lending standards vary through time due to strategic interaction between competing banks. Credit cycles can occur without any change in the macroeconomic environment.

We then go on to empirically investigate this lending standard model, providing empirical evidence that bank credit cycles are an important autonomous part of business cycle dynamics. Empirical tests take advantage of the unique information environment in U.S. banking, where detailed information about rival banks is collected and released periodically by the bank regulators. Thus, the information that is the basis for banks' beliefs about rival banks' lending standards is observable to the econometrician. This allows for a novel approach to testing the repeated game. We propose direct measures of the information that the theory suggests are relevant for banks' beliefs. We use these measures as proxies for the beliefs themselves and show how these proxies drive the credit cycle.

Bank lending is clearly an important topic. Changes in bank credit allocation, sometimes called "credit crunches", appear to be an important part of macroeconomic dynamics. Bank lending is procyclical.<sup>1</sup> Rather than change the price of loans, the interest rate, banks sometimes

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

ration credit.<sup>2</sup> 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% in 1989 to less than 16% in 1994. At the same time, the share of assets invested in government securities increased from just over 15% to almost 25%.<sup>3</sup> 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.<sup>4</sup> The most direct evidence comes from the Federal Reserve System’s Senior Loan Officer Opinion Survey on Bank Lending Practices.<sup>5</sup> Banks are asked whether their “credit standards” for approving loans (excluding merger and acquisition-related loans) have “tightened considerably, tightened somewhat, remained basically unchanged, eased somewhat, or eased considerably”. Lown and Morgan (2005) examine this survey evidence and note that, except for 1982, every recession was preceded by a sharp spike in the net percentage of banks reporting a tightening of lending standards. Other evidence that bank lending standards change is econometric. Asea and Blomberg (1998) examined a large panel data set of bank loan terms over the period 1977 to 1993 and “demonstrate that banks change their lending standards—from tightness to laxity—systematically over the cycle” (p. 89). They concluded that cycles in bank lending standards are important in explaining aggregate economic activity.

Also in a macroeconomic context, changes in the Fed Lending Standards Index (the net percentage of respondents reporting tightening) Granger causes changes in output, loans, and the federal funds rate, but the macroeconomic variables are not successful in explaining variation in the Lending Standards Index.<sup>6</sup> The Lending Standards Index is exogenous with respect to the other variables in the Vector Autoregression system. See Lown and Morgan (2002, 2005) and Lown, Morgan and Rohatgi (2000).<sup>7</sup> The analysis in this paper is aimed at explaining the forces that cause lending standards to change and, in particular, to explain how this can happen independently of macroeconomic variables.

To investigate bank lending standards we construct a model of bank lending that is predicated on the special features of banks, namely, that banks produce private information about

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 (1994) 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 (2003) 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 seniority and experience, the banks’ hierarchy of decision-making, and so on.

5. The survey is conducted quarterly and covers major banks from all parts of the U.S., accounting for between 60% and 70% 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. Lown and Morgan (2002, 2005) use the survey results to create an index: the number of loan officers reporting tightening standards less the number of reporting loan officers reporting easing standards divided by the total number reporting.

7. 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.

potential borrowers when they determine whether borrowers meet their lending standards. Broecker (1990) emphasizes that this information asymmetry means that banks compete with each other in a special way. 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.<sup>8</sup> We study a repeated model of bank competition, à la Green and Porter (1984), 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.<sup>9</sup> A bank can strategically produce more information than its rivals and then select the better borrowers, leaving unknowing rivals with adversely selected loan portfolios. Unlike standard models of imperfect competition, following Green and Porter (1984), there are no price wars among banks since banks do not change their loan rates. However, as in Green and Porter (1984), inter-temporal 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.

Repeated games are difficult to test and that is the case here.<sup>10</sup> There are many equilibria, depending on agents’ beliefs. Agents’ beliefs about other agents’ beliefs depend on current information and the history of the game. We empirically determine the equilibrium, that is, “test” the model, by parameterizing the public information that is the basis for banks’ beliefs about rivals’ strategies and using such measures as proxies for beliefs. The empirical behaviour 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, our belief proxy, called the Performance Difference Index (PDI), as explained later, 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.

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

8. In Broecker’s (1990) model, banks use noisy, independent, creditworthiness tests to assess the riskiness of potential borrowers. Because the tests are imperfect, banks may mistakenly grant credit to high-risk borrowers whom 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.

9. Strategic interaction between banks seems natural because banking is highly concentrated. Entry into banking is restricted by governments. In developed economies the share of the largest five banks in total bank deposits ranges from a high of 81.7% in Holland to a low of 26.3% in the U.S. See the Group of Ten (2001). In less developed economies, bank concentration is typically much higher (see Beck, Demirguc-Kunt and Levine, 2006).

10. Empirically testing models of repeated strategic interaction of firms has focused on price wars. See Reiss and Wolak (2007) and Bresnahan (1989) for surveys of the literature. However, our model predicts that there are “information production wars”. Since information production is unobservable, we cannot follow the usual empirical strategy. We propose a new method for empirically investigating such models.

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

Second, we turn to the macroeconomy by looking at commercial and industrial loans. We analyse a number of macroeconomic time series, including the Lending Standard Survey Index. We form an aggregate bank PDI based on the absolute value of the differences on all commercial and industrial loans of the largest 100 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 behaviour of the Lending Standard Survey responses (the percentage of banks reporting "tightening" their standards).

Finally, if credit crunches are endogenous, and a systematic risk, then they should be a priced factor in an asset pricing model of stock returns. Therefore, our final test is to ask whether a mimicking portfolio for our parameterization of banks' relevant histories is a priced risk factor in a Capital Asset Pricing Model (CAPM) or Fama–French asset pricing setting. We look at banks and non-financial firms by size, as credit crunches have larger effects on smaller firms. We find the evidence to be consistent with the theory.

Two related theoretical models are provided by Dell'Ariccia and Marquez (2006) and Ruckes (2004). 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 behaviour in our paper is purely driven by the strategic interactions between banks instead of an exogenously changing economic environment.

In terms of empirical work, Rajan (1994) is related. He argues that fluctuations in credit availability by banks are driven by bank managers' concerns for their reputations (due to bank managers having short horizons) and that consequently bank managers are influenced by the credit policies of other banks. Managers' reputations suffer if they fail to expand credit while other banks are doing so, implying that expansions lead to significant increases in losses on loans subsequently.<sup>11</sup> We test Rajan's idea in the empirical section.

Also related to our work, though more distantly, is some research in Monetary Theory, in particular on the "bank lending channel".<sup>12</sup> The "bank lending channel" posits that disruptions in the supply of bank loans can be caused by monetary policy, resulting in credit crunches (see Bernanke and Blinder, 1988). If bank funding is interest rate sensitive, then perhaps changes in banks' cost of funds results in variation in the amount of credit that banks supply. The bank lending channel is controversial because, as some have argued, banks have access to non-deposit sources of funds. See Ashcraft (2006) for evidence against the bank lending channel. We do not investigate the effects of monetary policy here, though this is a topic for future research. We provide the micro-foundations for how bank competition can cause credit crunches independent of monetary policy, but this is not mutually exclusive from the bank lending channel. However, like the bank lending channel literature, we assume that there are no perfect substitutes for bank

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

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

loans, so that if borrowers are cut off from bank credit they cannot find alternative financing at the same price, especially small firms. Large firms usually have access to capital markets.

We proceed in Section 2 to first describe the stage game for bank lending competition, and we study the existence of stage Nash equilibrium and the model's implications for lending standards, and the stage game is followed by repeated competition. In Section 3, we carry out empirical tests in the credit card loan market, a market dominated by a small number of banks. In Section 4 we extend the empirical analysis to commercial and industrial loans, the most important category of loans. We test whether our model can explain credit crunches. Section 5 undertakes a different type of test. We ask whether the risk caused by bank strategic behaviour is priced in an asset pricing context. Finally, Section 6 concludes the paper.

## 2. THE LENDING MARKET GAME

We first set forth the lending market stage game. To simplify our discussion, suppose that there are two banks in the market competing to lend, as follows. There are  $N$  potential borrowers in the credit market. Each of the potential borrowers is one of two types, good or bad. Good types' projects succeed with probability  $p_g$ , and bad types' projects succeed with probability  $p_b$ , where  $p_g > p_b \geq 0$ . Potential borrowers, sometimes also referred to below as "applicants", do not know their own type. At the beginning of the period potential borrowers apply simultaneously to each bank for a loan. There is no application fee. The probability of an applicant being a bad type is  $\lambda$ , which is common knowledge.<sup>13</sup> 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, that is, a borrower's realized cash flow is verifiable.

Banks are risk neutral. They can raise funds at some interest rate, assumed to be 0. After receiving the loan applications, a bank can use a costly technology to produce information about the applicant's type. The creditworthiness testing results in determining the type of an applicant, but there is a per applicant cost of  $c > 0$ . Banks can test any proportion of their applicants. Let  $n_i$  denote the number of applicants that are tested by bank  $i$ . We say that the more applicants that a bank tests, using the costly information production technology, the higher are its credit or lending standards.<sup>14</sup> If a bank switches from not using the creditworthiness test to using it, or tests more applicants, we say that the bank has "raised" its lending or credit standards. We assume that neither bank observes the other bank's credit standards, that is, 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 0, 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 creditworthiness testing. We assume

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

Assumption 1 means that there exists some interest rate,  $X$ , that allows a bank to earn positive profits from lending to a good type project *ex ante*, but there does not exist an interest

13. We will hold  $\lambda$  fixed throughout the analysis, but this is to clarify the mechanism that is our focus. It is natural to think of  $\lambda$  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.

14. 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 creditworthiness test as the additional information produced, beyond the normal information production.

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 (possibly none, possibly 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 A. 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 loan outcomes (*i.e.* default or not) are publicly observable. Banks cannot communicate with each other. Figure 1 shows the timing of the stage game.

### 2.1. Stage Nash equilibrium

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

First we will study the Nash equilibrium in which no bank conducts creditworthiness testing. The following assumption guarantees the existence of such equilibria.

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

Assumption 2 also implies that the optimal pay-offs for the banks are reached when no creditworthiness testing are conducted (as we will show later).

**Proposition 1.** *Under Assumption 2, there exists a symmetric Nash equilibrium in which no bank conducts creditworthiness testing and both banks earn zero profits.*

The proof is in Appendix B.

Proposition 1 says that if the cost of testing each loan applicant is sufficiently high, then there exists a Nash equilibrium in which no bank conducts creditworthiness testing and neither bank earns positive profits.

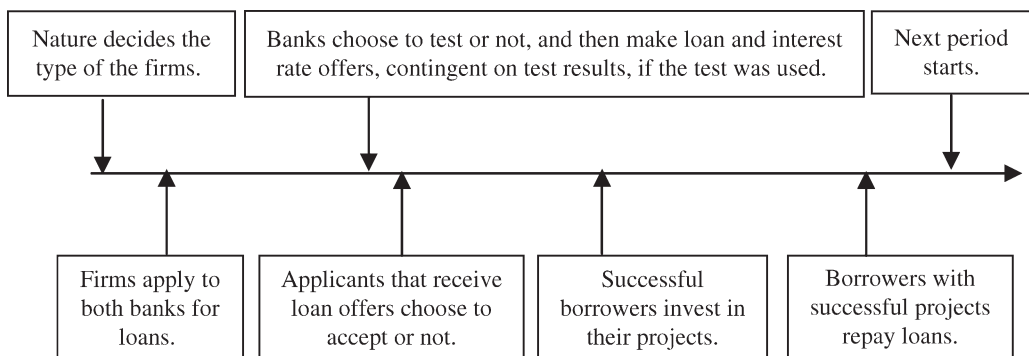


FIGURE 1  
The timing of the stage game



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

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

The proof is in Appendix C.<sup>15</sup>

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 0. 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 creditworthiness testing and both banks earn zero profits.

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

## 2.2. Repeated competition

We formalize the repeated game in Appendix D. In the stage game, we have already shown that banks earn zero profits without testing, and the optimal pay-offs for banks are reached when there is no costly creditworthiness test being used. Setting a (collusive) loan interest rate of  $F = X$  would be the most profitable case for both banks. Ideally, in repeated competition banks will try to collude to charge  $F = X$  without conducting creditworthiness 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 inter-temporal 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 creditworthiness 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 creditworthiness testing, the expected pay-off 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 pay-off to the bank is  $\pi'' = \lambda[\lambda p_b F + (1 - \lambda_g F) - 1] + (1 - \lambda)(p_g F - 1) - c$ . The difference between  $\pi''$  and  $\pi$  is  $\lambda(1 - \lambda)(p_g - p_b) F - c$ , which is increasing with  $F$ . When there are multiple applicants, while benefiting from finding a good type applicant through a creditworthiness test, a bank will switch to an untested applicant if the tested one turns out to be of bad type, and this substantially improves the net gain from a creditworthiness test. Therefore, when  $F$  is high enough, banks will have an incentive to produce information while manipulating the loan portfolio size through interest rates. To proceed, we make the following assumption:

15. 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.

**Assumption 3.**  $c \leq \lambda(1 - \lambda)(p_g - p_b)X$ .

This assumption guarantees that when banks collude at the highest possible interest rate,  $X$ , they have incentive to over-produce information and undercut interesting rates.

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.

At a profitable interest rate, if a bank makes more loans than its rival, then the continuation value of this bank should be lower, to eliminate the incentive of the banks to deviate by undercutting interest rates to get more loans. However, when there is creditworthiness testing, it may not be true that making more loans is always better. A bank can deviate by testing, "raising credit standards", resulting in the other bank lending to 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, it is easy to imagine (and we can formally show) that loan performance (number of defaults in each bank portfolio) will also affect the continuation value. When the banks want to avoid costly creditworthiness testing on the equilibrium path, then it is not possible for the two banks to collude on a high loan interest rate in equilibrium without looking at each other's loan performances. The possibility of deviating by using creditworthiness 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.

To demonstrate that monitoring through loan size only is not sufficient to detect a deviation, let us first look at an example with two loan applicants, where each bank makes a loan offer to both loan applicants at interest rate  $F_\alpha > F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g}$  without a creditworthiness test. Consider a deviation to a strategy 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  $F_\alpha^-$  for the loan to the other applicant. If the tested applicant is a good type then the bank offers a loan to the applicant at  $F_\alpha^-$  and raises the interest rate to  $F_\alpha^+$  for the loan to (or rejects) the other 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  $\Delta E[\pi] > 0$  as long as  $F_\alpha$  is close enough to  $X$ , by Assumption 3.

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 0.25, (1, 1) with probability 0.5, and (0, 2) with probability 0.25. Let  $u_i(n_1, n_2)$  denote the pay-off to bank  $i$  when the loan allocation is  $(D_1, D_2)$ , and we know by Lemma 5 in Appendix E that, in a Symmetric Perfect Public Equilibrium (SPPE):

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

which implies

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

Thus with the deviation, the expected continuation pay-off remains unchanged. We can show that this result holds with more than two applicants for any SPPE, as defined in the appendix; we omit the proof here for brevity.

Therefore, in order to detect banks' deviations through overproduction of information, banks' strategies need to depend on the public histories of banks' loan portfolio performances and portfolio sizes. However, the theory does not provide details on how the public histories are



linked to banks' beliefs and strategies. To help understand this issue for later empirical tests, let us again 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  $F_\alpha$  to both of them) to strategy  $s'$  as follows: test one applicant; if he is good, offer a loan at rate  $F_\alpha^-$ , and reject the other applicant; if the applicant is bad, reject it, and offer a loan to the other applicant at loan rate  $F_\alpha^-$ . In this way, the expected loan portfolio size is not changed, but loan performance will be improved; there is less likely to be a default. Given the loan distribution ( $D_1 = 1, D_2 = 1$ ), from Bank 2's point of view, without deviation by Bank 1, the probability of Bank 2 having a loan default is

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

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

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

The likelihood of default is higher by

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

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

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

With Bank 1 deviating to strategy  $s'$ , this probability becomes

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

We have

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

Therefore, compared with punishing each other after a bad performance, doing that after a relatively bad performance incurs a smaller probability of a mistaken punishment ( $q_r < q$ ), while it generates the same incentive to not to deviate ( $\Delta q_r = \Delta q$ ). 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, and which does not differentiate our story from other alternative stories, such as learning effect.

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 offer loans to those that pass the test. To simplify the argument, assume that the interest rates offered to non-tested applicants are higher than the one offered to applicants that passed the test. For the non-tested applicants, it is possible that there does not exist a profitable interest rate due to the winner's curse. If a bank offers loans to non-tested applicants, then given an offer is accepted by an applicant, the probability of this non-tested applicant being a bad type is

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

When  $n$  is close to  $N$ ,  $\theta$  can be very close to 1. When banks conduct creditworthiness 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 cannot get loans if both banks test a large portion of all applicants. This is a “credit crunch” in which applicants not tested by either bank are denied loans, even if they are in fact good types.

The above discussions lead to our empirical tests in the next section: banks’ relative performance is important for the credit cycles, which have a significant impact on the economy. In normal periods, banks produce information about borrowers at the optimal level, and they trigger the punishment phase by overproducing information after observing an abnormal difference in loan performance. The overproduction of information leads to credit crunches. More specifically, banks will observe the relative performance differences with respect to loan portfolio size and loan defaults in the portfolio. Their beliefs about the rival banks’ credit standards are based on this information. Our empirical tests are based on using measures of this information as proxies for bank beliefs.

### 3. EMPIRICAL TESTS: CREDIT CARD LOANS

In the model banks form beliefs based on public information. While we cannot measure beliefs directly, we can measure the information used to form beliefs. Our measures are proxies for bank beliefs. The empirical strategy we adopt is to focus on one robust prediction that the theory puts forward, namely, that unlike a perfectly competitive lending market, in the imperfectly competitive lending market that we have described, public histories about rival banks should affect the decisions of any given bank. We construct measures of the relative performance histories of banks, variables that are at the root of beliefs and their formation. In particular, changes in beliefs about rival behaviour 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 U.S. bank regulatory authorities (the Federal Reserve, Federal Deposit Insurance Corporation, and the Office of the Comptroller of Currency) in the quarterly Call Reports of Condition and Income (“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 PDIs based on the Call Reports that U.S. banks file quarterly to bank regulators. These reports are filed by banks within 30 days after the last business day of the quarter, and become public roughly 25–30 days later.<sup>16</sup> For that reason, we try to use more than one lag when we analyse the predictive power of certain variables to be constructed based on the Call Reports. Because the reports appear at a quarterly frequency, we analyse 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, that is, when there is a greater dispersion of relative performance, then all rival banks

16. 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 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.

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 artefact 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.

### 3.1. *The credit card loan market*

We first examine a specific, but important category of loans, credit card loans.<sup>17</sup> 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 1991.1 through 2006.3 for “Credit Cards and Related Plans”, as well as some other variables discussed below.<sup>18</sup>

The high concentration is shown by the Herfindahl Index for bank holding companies as well as the market share of top bank holding companies in Figure 2.

We can see from Figure 2 that over time the credit card loan market has become increasingly concentrated; the Herfindahl Index and the market share of the top bank holding companies have become much larger.

### 3.2. *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 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 1991.1 to 2006.3 for “Credit Cards and Related Plans (LS)”, we also use “Charge-offs on Loans to Individuals for Household, Family, and Other Personal Expenditure—Credit Cards and Related Plans (CO)”, “Recoveries on Loans to Individuals for Household, Family, and Other Personal

17. 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.

18. The data are not reported more frequently than quarterly.

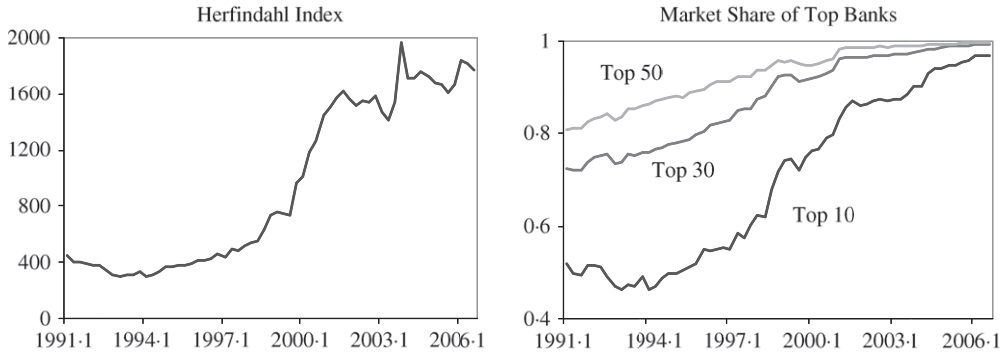


FIGURE 2

Market concentration in credit card loan market

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

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

$$\text{Ratio of Credit Card Loans to Total Loans (LR)} = \text{LS} / \text{TL}.^{19}$$

With respect to macroeconomic data we use quarterly macroeconomic data from the Federal Reserve Bank of St Louis for the period 1991.1 to 2006.3: “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*)”.<sup>20</sup>

### 3.3. Pairwise tests of rival banks

We start by looking at banks pairwise. We do this for two reasons. First, it is not known which banks are rivals, and it may be that not all banks are rivals despite the fact that they are all major credit card lenders.<sup>21</sup> Second, we only have less than 60 quarterly observations for each bank, so examining several banks jointly (including lags of each individual bank’s performance) quickly uses up the degrees of freedom. We focus on the largest six bank holding companies, which constantly remain within the top 20 in credit card loan portfolio size during the period 1991.1 to 2004.2.<sup>22</sup> These six banks are JP Morgan Chase, New York, NY (*CHAS*) (*CHAS*); Citicorp, New York, NY (*CITI*); Bank One Corp., Chicago, IL (*BONE*); Bank of America, Charlotte, NC (*BOAM*), MBNA Corp., Wilmington, DE (*MBNA*); and Wachovia Corp., Winston-Salem, NC (*WACH*).

19. Before 2001, there are two categories in Consumer Loans: Credit Card Loans & Related Plans and Other Consumer Loans. Since 2001, there are three categories in Consumer Loans: (i) Credit Card Loans, (ii) Other Revolving Credit Plans, and (iii) Other Consumer Loans. However, since 2001, the loan loss information (charge offs and recoveries) is reported in two categories, for (i) and (ii)+(iii) respectively. Starting from 2001, we construct Loan Loss Ratio (*LL*) with information on Credit Card Loans only, while the Credit Card Loan Ratio (*LR*) is constructed using Credit Card Loans and Other Revolving Credit Plans to be consistent with before 2001.

20. 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*.

21. For example, individual banks may dominate certain clienteles or geographical areas.

22. Data for Wachovia stops at 2001.2, as its credit card loans are managed by MBNA after that. However, the credit card loans from Wachovia do not appear in MBNA’s balance sheet. After 2004.2, Bank One is acquired by JP Morgan Chase, so we do not use the data after that.

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

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

where

$$y_{it} = \text{LL}_{it} \text{ or } \text{LR}_{it}, x_{it} = (\text{C}, \text{DPI}_t, \text{UMP}_t, \text{LL}_{it-1}, \text{LL}_{it-2}, \text{LL}_{it-3}, \text{LL}_{it-4}),$$

$$z_{ijt} = (|\Delta\text{LL}_{ijt-1}|, |\Delta\text{LL}_{ijt-2}|, |\Delta\text{LL}_{ijt-3}|, |\Delta\text{LL}_{ijt-4}|),$$

and  $\alpha_{ij}$  and  $\beta_{ij}$  are the coefficients for  $x$  and  $z$ , respectively. Adding lags of DPI or UMP do not change our major results. Since some bank holding companies might have systematically higher (or lower) loan loss rates than other bank holding companies, we first take out the mean from the loan loss ratio of each bank, and then take the difference to get  $\Delta\text{LL}_{ij}$ . In this way,  $|\Delta\text{LL}_{ij}|$  reflects the relative performance of the two banks.

$|\Delta\text{LL}_{ij}|$  is the key variable. It is a particular parameterization of the relevant public information: the performance difference. Conditional on the state of the economy and bank holding company  $i$ 's own past performance, we ask whether bank holding company  $i$ 's lending decisions depend on the observed absolute value of the differences between its own past performance and that of its rival, bank holding company  $j$ . Our theory predicts that, when  $|\Delta\text{LL}_{ij}|$  and its lags are large, the bank will (implicitly) raised lending standards, resulting in fewer loans in the future and lower losses per dollar loaned. So, the coefficients are predicted to be negative. For each measure of the relative difference in loan performance, we test whether the vector of coefficients on  $z_{ijt}$  (the  $\beta$ 's) is 0, that is,  $\beta = 0$ , using a Wald test (chi-squared distribution).

An important issue with the above approach of pairwise regressions is 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 pairwise regression results 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; that is,

$$H_0 : y_{it} = \alpha_i x_{it} + u_{it}.$$

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

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

In order to test the null hypothesis, we first construct a Significance Index, SI, and then use the bootstrap to obtain an approximation to the distribution of the SI under null hypothesis to find the  $p$ -value of the SI from the pairwise regressions using the original data, SI\*. The details of the bootstrap procedure are contained in Appendix F.

The results of the pairwise regressions and the bootstraps are reported in Table 1. With the bootstrap we can address the question of the likelihood that adding PDI to the model will yield the same number of significant coefficients as with the real data. The results show that this probability is low; therefore the null hypothesis (that PDI is unimportant) is rejected. See the  $p$ -values for the SI shown in Table 1.

An alternative explanation is that banks learn about the underlying economic conditions from other banks' loan performance. Perhaps this learning effect is also captured by the  $|\Delta\text{LL}_{ij}|$  variable that we constructed. It would seem that learning should not be based on absolute differences in bank performance, but on the level of other banks' performances as well as the bank's





own performance history. To examine this possibility we add lags of  $LL_j$  in the regression of Bank  $i$ . Therefore, in the regression equation (1), we replace  $x_{it}$  with  $x_{ijt}$ :

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

The results for learning effect are also reported in Table 1.

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

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

### 3.4. An aggregate PDI

Based on the success of the pairwise tests, we move next to analysing the histories of all relevant rival credit card lenders jointly. We construct an aggregate PDI:

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

This PDI measures the average difference of the competing banks' loan performances. Again, we first take out the mean from each  $LL_i$ , and then take the difference. For each bank  $i$ , we estimate the following model:

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

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

In a more restrictive environment, we estimate a pooling regression model with the restriction  $\beta_i = \beta$  for  $i = 1, \dots, 6$ . The results are also reported in Table 2.

From Panel A and C in Table 2, we observe that most coefficients are negative, consistent with our conjecture from the theory. When there is a large performance difference across all the rival banks, banks raise their lending standards to punish each other, and consequently future loan losses and loan ratios go down. In particular, in regressions with  $y_{it} = LL_{it}$ , the coefficients for JP Morgan Chase, Bank of America, and Wachovia are statistically significant; in regressions with  $y_{it} = LR_{it}$ , the coefficients for Citicorp, Bank One, and Bank of America are statistically significant. In our pooling regressions, the significance of our PDI is improved.

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

TABLE 2

This table contains the results for Performance Difference Index (PDI) regressions. In Panel A and C, for each bank, we run the regression:  $y_{it} = \alpha_i x_{it} + \beta_1 z_t + \varepsilon_{it}$ , with  $y_{it} = LL_{it}$  or  $LR_{it}$ ,  $x_{it} = (C, UMP, DPI, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4})$  and  $z_t = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$ . In Panel B and D, we pool the data of six banks together and estimate the system with the restriction that  $\beta$ s are the same across banks:  $y_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$ , with  $y_{it} = LL_{it}$  or  $LR_{it}$ ,  $x_{it} = (C, UMP, DPI, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4})$  and  $z_t = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$  for  $i = 1, \dots, 6$ . The system is estimated using Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) methods. We report the coefficients on  $z_t$  as well as their  $t$ -statistics

	Panel A																								
	CHAS			CITI			BONE			BOAM			MBNA			WACH			OLS			SUR			
	Coeff.	$t$ -stat		Coeff.	$t$ -stat		Coeff.	$t$ -stat		Coeff.	$t$ -stat		Coeff.	$t$ -stat		Coeff.	$t$ -stat		Coeff.	$t$ -stat		Coeff.	$t$ -stat		
$y_{it} = LL_{it}$																									
$PDI_{t-1}$	-0.942	-2.10		-0.279	-0.50		-1.392	-1.42		-1.380	-2.48		-0.089	-0.47		-0.679	-3.13		-0.818	-4.30		-0.563	-4.38		
$PDI_{t-2}$	0.039	0.09		0.140	0.27		-0.786	-0.81		-0.040	-0.07		0.080	0.41		-0.393	-1.65		-0.169	-0.88		-0.202	-1.51		
$PDI_{t-3}$	0.161	0.35		0.161	0.31		0.135	0.14		0.099	0.17		-0.005	-0.03		-0.048	-0.20		-0.028	-0.14		-0.017	-0.13		
$PDI_{t-4}$	-0.098	-0.22		-0.117	-0.24		-1.100	-1.19		-0.453	-0.75		0.095	0.53		-0.546	-2.31		-0.341	-1.81		-0.036	-0.27		
$R^2$	0.77			0.75			0.83			0.71			0.88			0.83									
$y_{it} = LR_{it}$																									
$PDI_{t-1}$	0.144	0.30		-1.746	-2.48		-1.880	-0.78		-0.710	-2.45		0.616	0.52		0.933	0.12		-0.535	-1.32		-0.403	-2.23		
$PDI_{t-2}$	-0.068	-0.14		-1.407	-2.16		-3.784	-1.58		-0.386	-1.33		-0.353	-0.29		-0.498	-0.58		-0.823	-2.02		-0.578	-3.19		
$PDI_{t-3}$	-0.214	-0.44		-1.557	-2.40		-3.826	-1.61		-0.315	-1.04		-0.697	-0.57		-0.727	-0.83		-1.149	-2.79		-0.665	-3.57		
$PDI_{t-4}$	0.187	0.39		-1.579	-2.60		-5.909	-2.61		-0.862	-2.74		1.030	0.92		-0.578	-0.67		-0.932	-2.32		-0.741	-4.02		
$R^2$	0.74			0.89			0.75			0.92			0.88			0.83									

Coeff., coefficients;  $t$ -stat,  $t$ -statistic.

are  $-0.786$  and  $-3.850$ . The mean of LL and LR are  $0.0316$  and  $0.0911$ . When PDI changes by one S.D., LL decreases by  $0.00357$  (11% of the mean), and LR decreases by  $0.0175$  (19% of the mean).

### 3.5. 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 PDI has predictive power for the stock returns of each top bank holding company in credit card loans. We collect the stock returns from CRSP from 1991.1 to 2004.2. We carry out the tests for all six bank holding companies. According to our theory, after observing large performance differences between banks, banks will raise their lending standards (which is costly), and cut lending. Consequently, their profit margins will be lower. Therefore, we expect to see negative loadings on the lags of the PDI. Note that this is not an asset pricing model, but a test concerning bank profits, as measured by stock returns. The regression equations are

$$r_{it} = \alpha_i + \beta_i z_t, \quad i = 1, \dots, 6, \quad (3)$$

where  $z_t = (\text{PDI}_{t-1}, \text{PDI}_{t-2}, \text{PDI}_{t-3}, \text{PDI}_{t-4})$ .

Since the dividend yield is well known to be a predictor of future stock returns (see, for example, Cochrane, 1999), we also estimate the model with the lag of dividend yield as a predicting variable. Again, robustness is checked by imposing the restriction  $\beta_i = \beta$  for  $i = 1, \dots, 6$ . All the results are reported in Table 3.

From Table 3, we see that the PDI from the previous four quarters significantly predicts the stock return for the current quarter, and the results are robust if we include a lag of the dividend yield in the regressions. The average coefficient on the lags of PDI from OLS estimates is about  $-3.5$ . One S.D. change in PDI ( $0.00454$ ) leads to an average change of  $0.0159$  in stock returns, or 159 basis points!

### 3.6. 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).<sup>23</sup> In the context here the question is whether our measure of banks' beliefs about rivals' credit standards, the PDI, remains significant in the presence of an average or aggregate credit card loss measure. We construct

$$\text{Aggregate Credit Card Loan Loss (AGLL}_t) = \frac{\sum_i (\text{CO}_{it} - \text{RV}_{it})}{\sum_i \text{LS}_{it}},$$

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

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 favour of Rajan's theory.

TABLE 3

*This table contains the results for the predictive power of Performance Difference Index (PDI) for stock returns. In Panel A and C, for each bank, we run the regression:  $r_{it} = \alpha_i x_{it} + \beta_1 z_t + \beta_2 z_t + \varepsilon_{it}$ , with  $x_{it} = C$  or (C, DividendYield $_{it-1}$ ) and  $z_t = (PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$ . In Panel B and D, we pool the data of six banks together and estimate the system with the restriction that  $\beta_{15}$  are the same across banks:  $r_{it} = \alpha_i x_{it} + \beta_1 z_t + \beta_2 z_t + \varepsilon_{it}$ , for  $i = 1, \dots, 6$ . The system is estimated using Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) methods. We report the coefficients on  $z_t$  as well as their  $t$ -statistics*

With Dividend Yield	Panel A						Panel B: pooling					
	CHAS	CITI	BONE	BOAM	MBNA	WACH	OLS	SUR	OLS	SUR	OLS	SUR
	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat
PDI $_{t-1}$	-3.66	-0.75	3.53	0.66	1.46	0.39	1.35	0.36	-8.28	-1.60	-1.66	-0.48
PDI $_{t-2}$	-2.56	-0.53	-1.73	-0.32	-2.53	-0.67	-3.09	-0.82	1.56	0.30	-6.76	-1.95
PDI $_{t-3}$	-9.78	-2.02	-4.80	-0.90	-8.91	-2.37	-9.97	-2.63	-6.87	-1.33	2.00	0.57
PDI $_{t-4}$	-1.60	-0.32	-4.97	-0.91	-7.13	-1.86	-5.91	-1.53	-4.71	-0.90	-5.80	-1.65
R <sup>2</sup>	0.13		0.07		0.14		0.25		0.13		0.16	
With Dividend Yield	Panel C						Panel D: pooling					
	CHAS	CITI	BONE	BOAM	MBNA	WACH	OLS	SUR	OLS	SUR	OLS	SUR
	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat
PDI $_{t-1}$	-2.72	-0.54	4.62	0.80	4.38	1.28	1.13	0.29	-8.20	-1.56	-2.71	-0.74
PDI $_{t-2}$	-1.65	-0.33	-1.97	-0.36	-0.66	-0.20	-3.20	-0.84	1.65	0.31	-6.96	-2.00
PDI $_{t-3}$	-8.72	-1.72	-4.33	-0.79	-7.47	-2.24	-9.72	-2.53	-6.81	-1.30	0.59	0.15
PDI $_{t-4}$	-0.41	-0.08	-4.55	-0.82	-3.38	-0.95	-5.63	-1.44	-4.64	-0.87	-5.54	-1.56
R <sup>2</sup>	0.14		0.08		0.43		0.26		0.13		0.18	

Coeff., coefficients;  $t$ -stat,  $t$ -statistic.

TABLE 4

This table contains the results of testing Rajan's (1994) reputation hypothesis. In Panel A and C, we pool the data of six banks together and estimate the system:  $y_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$ , with  $y_{it} = LL_{it}$  or  $LR_{it}$ ,  $x_{it} = (C, UMP_t, DPI_t, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4})$  and  $z_t = (AGLL_{t-1}, AGLL_{t-2}, AGLL_{t-3}, AGLL_{t-4})$  for  $i = 1, \dots, 6$ . In Panel B and D, we pool the data of six banks together and estimate the system:  $y_{it} = \alpha_i x_{it} + \beta z_t + \varepsilon_{it}$ , with  $y_{it} = LL_{it}$  or  $LR_{it}$ ,  $x_{it} = (C, UMP_t, DPI_t, LL_{it-1}, LL_{it-2}, LL_{it-3}, LL_{it-4})$  and  $z_t = (AGLL_{t-1}, AGLL_{t-2}, AGLL_{t-3}, AGLL_{t-4}, PDI_{t-1}, PDI_{t-2}, PDI_{t-3}, PDI_{t-4})$  for  $i = 1, \dots, 6$ . The system is estimated using Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) methods. We report the coefficients on  $z_t$  as well as their  $t$ -statistics

$y_{it} = LL_{it}$	Panel A				Panel B			
	OLS		SUR		OLS		SUR	
	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat
AGLL <sub>t-1</sub>	-0.023	-0.40	-0.103	-1.82	0.085	1.46	0.036	0.66
AGLL <sub>t-2</sub>	-0.038	-0.64	-0.059	-1.03	0.110	1.84	0.088	1.56
AGLL <sub>t-3</sub>	0.097	1.65	0.028	0.49	0.212	3.47	0.145	2.48
AGLL <sub>t-4</sub>	0.323	5.66	0.265	4.77	0.316	5.61	0.263	4.86
PDI <sub>t-1</sub>					-0.892	-5.26	-0.895	-5.70
PDI <sub>t-2</sub>					-0.433	-2.40	-0.334	-2.01
PDI <sub>t-3</sub>					-0.312	-1.72	-0.296	-1.77
PDI <sub>t-4</sub>					-0.391	-2.25	-0.100	-0.63
$y_{it} = LR_{it}$	Panel C				Panel D			
	OLS		SUR		OLS		SUR	
	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat	Coeff.	$t$ -stat
AGLL <sub>t-1</sub>	0.102	0.51	0.043	0.38	0.094	0.49	0.080	1.01
AGLL <sub>t-2</sub>	0.196	0.98	0.166	1.47	0.212	1.09	0.187	2.33
AGLL <sub>t-3</sub>	0.228	1.14	0.131	1.15	0.247	1.23	0.172	2.09
AGLL <sub>t-4</sub>	0.340	1.75	0.267	2.44	0.313	1.69	0.211	2.78
PDI <sub>t-1</sub>					-0.192	-0.35	-0.222	-0.91
PDI <sub>t-2</sub>					-0.797	-1.35	-0.674	-2.57
PDI <sub>t-3</sub>					-1.165	-1.96	-0.835	-3.19
PDI <sub>t-4</sub>					-0.817	-1.44	-0.549	-2.15

Coeff., coefficients;  $t$ -stat,  $t$ -statistic.

The coefficients on  $z_t$  and their  $t$ -statistics are reported in Table 4, which also contains the results with the restriction that the coefficients on  $z_t$  are the same across bank holding companies.

Rajan's (1994) hypothesis is that an aggregate bad shock leads banks to raise their standards, so we would expect the coefficients on lags of AGLL to be significantly negative. However, as Table 4 shows, with or without PDI in the regressions, the coefficients on AGLL are mostly positive and significant, with a few exceptions. At the same time, the coefficients on lags of PDI remain negatively significant, even after we include lags of AGLL in our regression.

#### 4. AN AGGREGATE PDI FOR COMMERCIAL AND INDUSTRIAL LOANS

In this section we extend the empirical analysis beyond credit card lending at six banks to examine the commercial and industrial loan market at an aggregate level, and we probe the implications of the theory for macroeconomic dynamics. Commercial and industrial loans is the category of loans that covers lending to firms of all sizes and corresponds to the loans at issue when there is a

credit crunch. If banks increase their information production, that is, raise their lending standards, then some borrowers are cut off from credit—a credit crunch that should have macroeconomic implications. We examine this with a vector autoregression in the first subsection. In the second subsection, we examine the PDI less formally to get a feel for what it measures.

#### 4.1. VAR analysis of the Fed's Lending Standards Index

In this subsection, we use Vector Autoregressions (VARs) to analyse 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. The Federal Reserve System's Senior Loan Officer Opinion Survey started in 1967.1, but was discontinued during the period 1984.1 to 1990.1.

We follow Lown and Morgan (2002, 2005) in analysing the time series of lending survey responses, the net percentage of banks reporting tightening in the survey.<sup>24</sup> As above, we use quarterly commercial and industrial loan data from the Chicago Federal Reserve Bank's Commercial Bank Database, which is from the Call Reports. For the period from 1984.1 to 2006.3, we collected "Commercial and Industrial Loans to U.S. Addressees" (LS), "Charge-Offs on Commercial and Industrial Loans to U.S. Addressees" (CO), and "Recoveries on Commercial and Industrial Loans to U.S. Addressees" (RV). For each commercial bank we constructed the Loan Loss Ratio (LL) :  $LL = \frac{CO-RV}{LS}$ .

We construct the PDI to measure the dispersion of performance across the U.S. banking industry as a whole. To do this, we use the top 100 commercial banks<sup>25</sup> ranked by commercial and industrial (C&I) loans, and for each quarter, we construct the PDI as  $PDI_t = \frac{\sum_{i>j} |LL_{it} - LL_{jt}|}{100 \times 99/2}$ . Besides the data on the Lending Standards and the PDI, we also collected data on Commercial and Industrial Loans at "All Commercial Banks and Federal Funds Rate" from the FRED II database of the St Louis Fed.<sup>26</sup> 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 creditworthiness tests.

The VAR includes four lags of the four endogenous variables: Bank Lending Standards (STAND) (*i.e.* the net percentage of survey respondents reporting tightening), the PDI, the Federal Funds Rate (FFR), and the log of Commercial Bank C&I Loans (LOGLOAN). The bank Lending Standard variable is a loan supply side factor and the Federal Funds Rate affects loan demand; Commercial Bank C&I Loan is the equilibrium outcome. The PDI is hypothesized to capture banks' beliefs, which affects all the other variables. The exogenous variables include a constant and a time trend. We run the VAR for the period of 1990.2–2006.3, which is the longest continuous period where we have both STAND and PDI data. We report the VAR results in Table 5.

24. Following Lown and Morgan (2002, 2005) we use the standards for large and middle-market firms. As mentioned, the Lending Standard Index is calculated as the net percentage of banks (all respondents) that report tightening.

25. We also construct the PDIs using the top 50 or top 200 commercial banks ranked by their C&I loan size; the results are similar.

26. We first collected monthly data and then took the three-month average to obtain quarterly data.



TABLE 5

*This table presents the average value of the coefficients and p-values (in parentheses) of the Wald test ( $\chi^2(4)$ ) of the VAR with four lags of the Lending Standard (STAND), the PDI, the Federal Funds Rate (FFR), and the log of Commercial Bank C&I Loan (LOGLOAN). The exogenous variables include a constant and a time trend*

	STAND	PDI	FFR	LOGLOAN
STAND	1.15E-01 (0.002)	2.19E-05 (0.004)	4.59E-04 (0.878)	-6.51E-05 (0.118)
PDI	8.10E+02 (0.037)	2.41E-01 (0.000)	-2.51E+01 (0.064)	-1.37E+00 (0.000)
FFR	1.70E-01 (0.315)	6.70E-05 (0.417)	2.01E-01 (0.000)	1.83E-03 (0.000)
LOGLOAN	2.52E+01 (0.044)	-6.27E-04 (0.416)	7.31E-02 (0.545)	2.39E-01 (0.000)

Table 5 shows that the PDI Granger causes the other three endogenous variables, and only STAND Granger causes PDI (actually none of the individual coefficients on STAND are significant, but they are jointly significant). For each of the other three endogenous variables, using the average coefficients on the lags of PDI, a one S.D. increase in PDI, 0.00319, leads to a 2.6% increase in net percentage of loan officers who claim to be raising the lending standards, a 78 basis point decrease in the federal funds rate, and a 0.44% decrease in C&I loans.

At the same time, the lending standards are significantly affected by PDI and LOGLOAN. A high level of performance differences causes a rise in lending standards, consistent with our theory of information production competition. Besides PDI, both STAND and FFR Granger cause LOGLOAN. To further explore the impact of PDI on other endogenous variables, we also report the forecasting error variance decomposition of our VAR in Table 6.

As we can see from Table 6, at a five-quarter horizon, innovations in STAND account for 13.9% of the error variance in the federal funds rate and 14.1% of the LOGLOAN error variance, while those numbers for PDI are 21.3% and 34.6%, respectively. At longer horizons, 10 quarters and 15 quarters, PDI continues to dominate STAND as a major variance contributor for FFR and LOGLOAN. Therefore, the PDI has a bigger impact than Lending Standards despite the fact that in our VAR the Lending Standards variable is ranked before the PDI variable. This confirms our view that PDI is a major economic indicator for bank competition, consistent with our information-based theory.

#### 4.2. Understanding the PDI

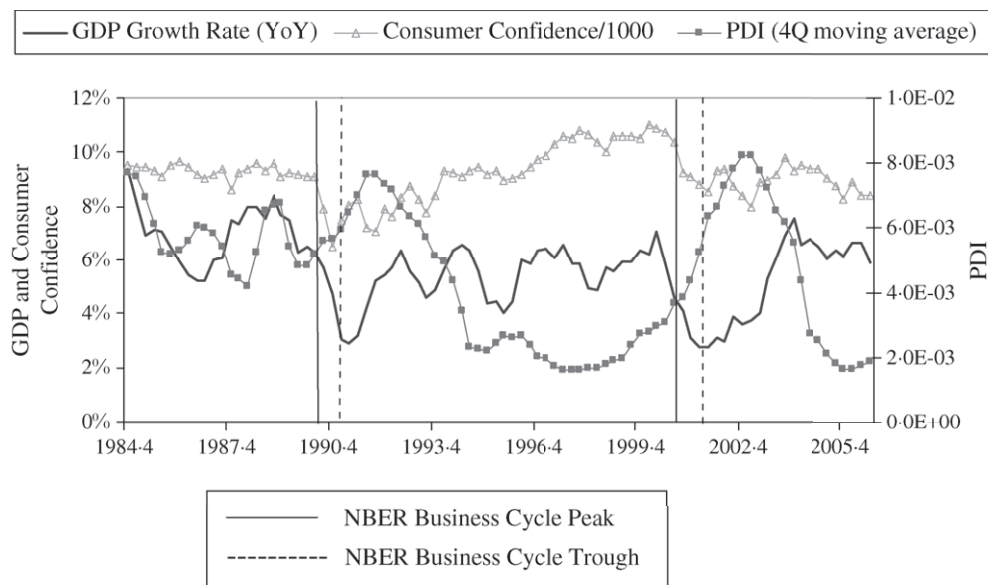
We can understand the PDI more intuitively by noting that a higher PDI is bad news for consumers, since credit lending standards will become more stringent and credit card loans will go down. This would apply also to other types of consumer loans, such as home equity loans, home improvement loans, automobile and boat loans, and so on. And it is bad news for firms, especially small firms, because lending standards will be raised, making commercial and industrial loans harder to obtain.

These broad implications are confirmed in Figure 3. The figure shows plots of the year-over-year change in U.S. GDP, the Michigan Consumer Confidence Index, and the four quarter moving average of PDI (based on C&I loans). At business cycle peaks, Consumer Confidence declines, and the year-over-year growth rate of GDP is going down. Notably, PDI is rising.

TABLE 6

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

Variance decomposition of STAND					Variance decomposition of PDI						
Period	S.E.	STAND	PDI	FFR	LOGLOAN	Period	S.E.	STAND	PDI	FFR	LOGLOAN
1	6.64	100.0	0.0	0.0	0.0	1	0.00094	0.2	99.8	0.0	0.0
3	8.03	89.5	2.9	6.9	0.8	3	0.00101	6.0	86.2	4.8	3.0
5	9.53	65.6	2.7	27.7	4.0	5	0.00134	14.5	76.6	6.5	2.4
10	11.13	50.0	13.6	32.6	3.8	10	0.00170	14.7	57.5	24.2	3.6
15	12.49	45.4	18.0	33.3	3.3	15	0.00188	14.1	58.6	23.2	4.1
Variance decomposition of FFR					Variance decomposition of LOGLOAN						
Period	S.E.	STAND	PDI	FFR	LOGLOAN	Period	S.E.	STAND	PDI	FFR	LOGLOAN
1	0.231	10.7	4.7	84.6	0.0	1	0.0050	23.8	0.5	8.1	67.7
3	0.527	10.6	12.5	76.1	0.8	3	0.0131	6.6	17.9	51.8	23.7
5	0.692	13.9	21.3	64.2	0.5	5	0.0212	14.1	34.6	40.8	10.5
10	0.869	12.9	27.2	57.6	2.3	10	0.0363	23.5	50.7	21.7	4.1
15	1.017	11.6	20.7	65.2	2.6	15	0.0519	25.1	32.4	39.0	3.5



Source: GDP and Consumer Confidence (University of Michigan Consumer Sentiment) data are from St Louis Fed website.

FIGURE 3  
PDI, consumer confidence, and GDP growth data

Correlation matrix (1984.1–2006.3)	$\Delta$ GDP	CC	STAND	PDI
GDP YoY Growth Rate ( $\Delta$ GDP)	1.00	0.33	-0.57	-0.37
Consumer Confidence (CC)	0.33	1.00	-0.09	-0.47
Lending Standards starting from 1990.2 (STAND)	-0.57	-0.09	1.00	0.46
Performance Difference Index (PDI) (Deseasoned)	-0.37	-0.47	0.46	1.00

These observations mean the PDI should be negatively correlated with Consumer Confidence (as measured by the University of Michigan Survey Research Center<sup>27</sup>) and PDI should be negatively correlated with aggregate economic activity. The table above shows the relevant correlations. (“YoY” means year-over-year.)

As expected, PDI is negatively correlated with consumer confidence and with the year-on-year GDP growth rate. As noted in the VAR analysis, PDI and lending standards are positively correlated.<sup>28</sup>

## 5. ASSET PRICING AND CREDIT CRUNCHES

Strategic competition between banks results in periodic credit crunches, which are a systematic risk even though endogenous. Consequently, if the stock market is efficient, then the stock returns

27. See <http://www.isr.umich.edu/src/>.

28. The credit card market and the commercial and industrial loan market need not display credit crunches at the same time, as banks may behave as if they are separate markets. The two PDI indices for these markets have a correlation of 0.18 after being deseasoned, and 0.46 before being deseasoned.

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 behaviour between banks causes credit cycles, then it causes variation in the profitability of non-financial firms. Credit crunches are also not profitable for banks. The credit cycle is a systematic risk (even if it is endogenous, emanating from bank competition) 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 PDI. Moreover, since relatively smaller firms are more dependent on bank loans (see, for example, Hancock and Wilcox, 1998), we expect that the coefficients on PDI (below, we construct the mimicking portfolio for this factor) are larger for smaller firms.

We adopt the classic Capital Asset Pricing Model as the benchmark for examining whether PDI is a priced factor. Later, we will also examine the Fama–French three factor empirical asset pricing model.<sup>29</sup> The model is estimated using quarterly data, as PDI can only be calculated quarterly.

We hypothesize that bank stock returns will be sensitive to PDI and that PDI is not spanned by the market factor. Further, non-financial firms' stock returns will also be sensitive, increasingly so for smaller firms, to PDI. 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 10 deciles based on the capitalizations. Banks are divided into small, medium, and large. The data used are from 1984.1 to 2006.3, during which the PDI is available.

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

We first regress the PDI factor on the excess returns of the 10 book-to-market sorted portfolios (either equal weighted or value weighted) and then construct the mimicking portfolio with the weight of each portfolio proportional to the regression coefficient on the excess return of this portfolio. Specifically, we first run the following regression:

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

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

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

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

and the excess return on the mimicking portfolio is given by

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

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

After we form the mimicking portfolio, we add it to the standard CAPM. The results are reported in Table 7. The results in Table 7 show that the PDI mimicking portfolio is a significant risk factor for small non-financial firms and for all bank sizes. Note that the coefficients on  $R_{\text{PDI}}$  for smaller firms are larger, thus confirming our conjectures. This is also confirmed by the monotonicity of the improvement in  $R^2$  with the new PDI factor.

In terms of the economic significance of the new PDI factor, the S.D. of  $R_{\text{PDI}}$  (constructed with value-weighted book-to-market portfolios) is 19.2% (this is quite large because the mimicking portfolio involves short positions). Therefore, when  $R_{\text{PDI}}$  changes by one S.D., the excess return for the smallest non-financial firms changes by about 3.3%. As a comparison, from 1984.1 to 2006.3, for Table 7 (CAPM), a one S.D. change of market excess return, 8.3%, results in the excess return for the smallest non-financial firms changing by about 9.3%. If we use equal-weighted book-to-market portfolios to construct our mimicking portfolio, one S.D. change of  $R_{\text{PDI}}$ , 29.1%, results in a 7.4% change of the excess return of the smallest non-financial firms, which is close to the impact of market excess return, 9.1%.

We conclude that the competition and collusion among banks is an important risk factor for stock returns, for banks and especially for small non-financial firms. The size effect further demonstrates that the PDI we constructed is not capturing some sort of learning effect about macroeconomic condition, which would be spanned by the other risk factors.

As a robustness check, we will also investigate the Fama–French three factor empirical asset pricing model. According to Fama and French, the sensitivity of a firm's expected stock return depends on three factors: the excess return on a broad based market portfolio,  $r_m - r_f$ ; the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (small minus large), SMB; the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (high minus low), HML.

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

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

TABLE 7

This table reports the results from estimating the augmented CAPM model:

$$r_i - r_f = \alpha + \beta_1(r_m - r_f) + \beta_2 R_{PDI} + \epsilon,$$

where  $R_{PDI}$  is constructed from 10 book-to-market portfolios, either equal weighted or value weighted. We report the coefficients and their  $t$ -statistics (in parentheses),  $R^2$  of each regression, and  $R^2$  of the regression without  $R_{PDI}$  (in parentheses)

Coefficient ( $t$ -stat)	$\alpha$	$r_m - r_f$	$R_{PDI}$	$R^2$ ( $R^2$ w/o $R_{PDI}$ )	$\alpha$	$r_m - r_f$	$R_{PDI}$	$R^2$ ( $R^2$ w/o $R_{PDI}$ )
	Commercial banks (using equal-weighted $R_{PDI}$ )				Commercial banks (using value-weighted $R_{PDI}$ )			
Small	1.988 (2.34)	0.456 (4.45)	0.119 (4.06)	0.33 (0.20)	2.227 (2.47)	0.447 (4.00)	0.109 (2.26)	0.25 (0.20)
Medium	2.131 (2.50)	0.589 (5.75)	0.118 (4.02)	0.40 (0.28)	2.388 (2.64)	0.584 (5.21)	0.102 (2.11)	0.32 (0.28)
Large	1.970 (2.89)	1.003 (12.22)	0.041 (1.75)	0.65 (0.64)	2.045 (2.97)	0.999 (11.67)	0.040 (1.09)	0.64 (0.64)
	Non-financial firms (using equal-weighted $R_{PDI}$ )				Non-financial firms (using value-weighted $R_{PDI}$ )			
Decile 1 (Small)	4.669 (3.22)	1.096 (6.29)	0.256 (5.14)	0.47 (0.31)	5.374 (3.33)	1.119 (5.58)	0.174 (2.00)	0.34 (0.31)
Decile 2	-0.523 (-0.48)	1.143 (8.73)	0.193 (5.17)	0.58 (0.45)	0.058 (0.05)	1.171 (7.72)	0.115 (1.76)	0.47 (0.45)
Decile 3	-0.662 (-0.71)	1.230 (10.90)	0.141 (4.39)	0.64 (0.56)	-0.238 (-0.23)	1.250 (9.86)	0.085 (1.55)	0.57 (0.56)
Decile 4	-0.762 (-0.87)	1.265 (12.04)	0.129 (4.31)	0.68 (0.61)	-0.340 (-0.36)	1.291 (10.93)	0.066 (1.30)	0.62 (0.61)
Decile 5	-0.196 (-0.25)	1.321 (13.99)	0.108 (3.99)	0.73 (0.68)	0.223 (0.26)	1.358 (12.87)	0.033 (0.71)	0.68 (0.68)
Decile 6	0.145 (0.20)	1.348 (15.22)	0.067 (2.67)	0.75 (0.72)	0.454 (0.59)	1.381 (14.54)	0.005 (0.13)	0.72 (0.72)
Decile 7	0.481 (0.82)	1.360 (19.39)	0.041 (2.04)	0.82 (0.81)	0.724 (1.22)	1.392 (18.83)	-0.015 (-0.48)	0.81 (0.81)
Decile 8	0.721 (1.55)	1.293 (23.12)	0.033 (2.09)	0.87 (0.86)	0.929 (1.95)	1.321 (22.41)	-0.015 (-0.60)	0.86 (0.86)
Decile 9	0.939 (2.81)	1.179 (29.29)	0.017 (1.48)	0.91 (0.91)	1.077 (3.20)	1.201 (28.73)	-0.018 (-1.02)	0.91 (0.91)
Decile 10 (Large)	1.113 (7.09)	0.982 (51.95)	-0.013 (-2.40)	0.97 (0.97)	1.067 (6.60)	0.979 (48.74)	-0.005 (-0.62)	0.97 (0.97)



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

After we form the mimicking portfolio, we add it to the Fama–French three-factor model. The results are reported in Table 8. The results in Table 8 also show that the PDI mimicking portfolio is a significant risk factor for small non-financial firms and for small banks, but not for large banks or large non-financial firms. Again, the coefficients on  $R_{PDI}$  for smaller firms are larger, as well as the improvement in  $R^2$  with the new PDI factor. Also, comparing Table 7 and Table 8, we can compare the improvement of  $R^2$  by adding our PDI factor with that by adding HML and SMB. For small non-financial firms,  $R^2$  improves from 0.31 to 0.47 by adding our PDI factor, and it improves from 0.31 to 0.57 by adding both HML and SMB, and further to 0.65 by adding our PDI factor. Therefore, we conclude that our PDI factor is not fully spanned by other factors and has a sizable explanatory power in our regressions.

As for the economic significance of  $R_{PDI}$ , when  $R_{PDI}$  (constructed with value-weighted book-to-market portfolios) changes by one S.D., the excess return for smallest non-financial firms changes by about 4.0% vs. 4.3% for the impact of market excess return. When we use  $R_{PDI}$  constructed with equal-weighted book-to-market portfolios, this number becomes 5.6%, which is larger than the impact of market excess return, 5.2%!

The magnitude of the coefficients on  $R_{PDI}$  in Table 8 is about the same as in Table 7, and this shows that without SML or HML in the regression, the PDI factor does not pick up higher loadings. This confirms that PDI risk factor represents an independent source risk, which cannot be spanned by SML or HML.

## 6. CONCLUSION

An important message of Green and Porter (1984) is that collusion can be very subtle. The subsequent theoretical work is very elegant and powerful. See Abreu, Pearce and Stacchetti (1990) and Fudenberg, Levine and Maskin (1994). Empirical work on testing models of repeated games, however, has been difficult because of the data requirements for estimation of structural models. Empirical work has been limited and has focused on price wars as the only examples of such imperfect competition. We presented a theoretical model of strategic repeated bank lending, in which banks compete in a rather special way, via the intensity of information production about potential borrowers. Based on prior information, for example, about bank loan interest rates being sticky, we conjectured which equilibrium occurred in reality. We then empirically tested the model by parameterizing the information on which banks' beliefs are based. The PDI are proxies for banks' beliefs.

We studied banking, an industry in which there have not been price wars. Banking is an industry with limited entry; it is a highly concentrated industry, and it is an industry that is informationally opaque and hence regulated. Banks produce private information about their borrowers, but they do not know how much information rival banks are producing. The information opaqueness affects competition for borrowers in that rivals can produce information with different precision. This causes the imperfect competition in banking to take a different form from other industries. In particular, we showed that the inter-temporal incentive constraints implementing the collusive arrangement (of high interest rates and low cost information production) require periodic credit crunches.

Because banking is regulated, bank regulators collect information from banks, and release it at periodic intervals. So, information about rival banks is made available by the government. All banks can see the performance of other banks. Our empirical approach to testing proceeds at the level of this 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

TABLE 8

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

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

where RpDI is constructed from 10 book-to-market portfolios, either equal weighted or value weighted. We report the coefficients and their *t*-statistics (in parentheses),  $R^2$  of each regression, and  $R^2$  of the regression without RpDI (in parentheses)

Coefficient ( <i>t</i> -stat)	Commercial banks (using equal-weighted RpDI)					Non-financial firms (using equal-weighted RpDI)						
	$\alpha$	$r_m - r_f$	SMB	HML	RpDI	$R^2$ ( $R^2$ w/o RpDI)	$\alpha$	$r_m - r_f$	SMB	HML	RpDI	$R^2$ ( $R^2$ w/o RpDI)
Small	1.578 (2.22)	0.489 (4.80)	0.587 (5.08)	0.613 (4.11)	0.060 (2.35)	0.55 (0.52)	1.631 (2.27)	0.449 (4.09)	0.603 (5.14)	0.718 (4.87)	0.071 (1.78)	0.54 (0.52)
Medium	1.689 (2.40)	0.639 (6.35)	0.622 (5.44)	0.592 (4.02)	0.058 (2.29)	0.61 (0.58)	1.760 (2.46)	0.609 (5.60)	0.644 (5.54)	0.690 (4.72)	0.059 (1.51)	0.59 (0.58)
Large	1.564 (2.51)	1.188 (13.28)	0.463 (4.57)	-0.098 (-0.75)	0.019 (0.82)	0.72 (0.72)	1.634 (2.61)	1.200 (12.57)	0.487 (4.77)	-0.073 (-0.57)	-0.003 (-0.08)	0.72 (0.72)
	Non-financial firms (using value-weighted RpDI)											
Decile 1 (small)	4.940 (4.08)	0.629 (3.63)	1.657 (6.53)	-0.042 (-0.21)	0.192 (4.37)	0.65 (0.57)	5.146 (4.04)	0.518 (2.67)	1.983 (7.60)	0.020 (0.10)	0.208 (2.96)	0.61 (0.57)
Decile 2	-0.398 (-0.50)	0.766 (6.76)	1.517 (9.15)	0.108 (0.84)	0.126 (4.41)	0.79 (0.74)	-0.256 (-0.31)	0.696 (5.47)	1.731 (10.13)	0.151 (1.11)	0.134 (2.90)	0.76 (0.74)
Decile 3	-0.534 (-0.89)	0.867 (10.04)	1.445 (11.44)	0.093 (0.95)	0.078 (3.57)	0.86 (0.84)	-0.495 (-0.81)	0.802 (8.59)	1.585 (12.64)	0.103 (1.03)	0.105 (3.11)	0.85 (0.84)
Decile 4	-0.702 (-1.31)	0.946 (12.28)	1.370 (12.15)	0.160 (1.83)	0.065 (3.34)	0.88 (0.87)	-0.649 (-1.18)	0.901 (10.74)	1.483 (13.16)	0.175 (1.96)	0.078 (2.58)	0.88 (0.87)
Decile 5	-0.120 (-0.27)	1.014 (15.80)	1.284 (13.68)	0.126 (1.73)	0.049 (3.01)	0.91 (0.91)	-0.049 (-0.11)	0.994 (14.10)	1.364 (14.41)	0.148 (1.75)	0.044 (1.75)	0.91 (0.91)
Decile 6	0.287 (0.90)	1.005 (20.90)	1.322 (19.68)	0.054 (1.03)	0.011 (0.97)	0.95 (0.95)	0.270 (0.85)	0.985 (20.33)	1.346 (20.66)	0.047 (0.91)	0.026 (1.46)	0.95 (0.95)
Decile 7	2.57 (2.57)	1.081 (32.08)	1.063 (21.57)	0.033 (0.86)	-0.004 (-0.43)	0.97 (0.97)	0.388 (2.50)	1.077 (30.05)	1.059 (21.98)	0.027 (0.72)	0.001 (0.11)	0.97 (0.97)
Decile 8	0.843 (4.27)	1.063 (37.60)	0.840 (20.32)	-0.003 (-0.03)	0.000 (-0.03)	0.98 (0.98)	0.842 (4.27)	1.063 (35.36)	0.840 (20.80)	-0.003 (-0.09)	0.000 (-0.00)	0.98 (0.98)
Decile 9	1.037 (5.54)	1.020 (37.97)	0.555 (14.14)	-0.023 (-0.75)	-0.004 (-0.59)	0.97 (0.97)	1.038 (5.55)	1.024 (35.89)	0.548 (14.29)	0.022 (-0.74)	0.007 (-0.64)	0.97 (0.97)
Decile 10 (Large)	1.184 (9.64)	0.985 (55.93)	-0.145 (-5.63)	-0.108 (-5.40)	-0.001 (-0.22)	0.98 (0.98)	1.178 (9.59)	0.983 (52.50)	-0.146 (-5.80)	-0.110 (-5.51)	0.001 (0.21)	0.98 (0.98)

differences has predictive power for rival banks' behaviour in the credit card market. Moreover, introducing the performance difference histories into a vector autoregression-type macroeconomic model, using commercial and industrial loans, confirms that this is an autonomous source of macroeconomic fluctuations.

Finally, since changes in bank beliefs based on public information cause credit cycles, this should be an important independent risk factor for stock returns, not only for banks, but also for borrowers. In an asset-pricing context this risk should be priced, even though it is endogenous. We showed that this is indeed the case. Smaller firms are more sensitive to this risk, confirming that such firms are more bank dependent.

As mentioned in the Introduction, one topic for future research is the effects of monetary policy on the repeated bank lending game. Another topic is to find and analyse other instances where the same empirical strategy can be applied. Appendices A–E contain details of the repeated lending game and proofs.

## APPENDIX A. FORMALIZATION OF THE STAGE STRATEGY

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

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

where:

- $n_i$ : the number of applicants that bank  $i$  tests;
- $N_{gi}$ : the number of good applicants found by bank  $i$  with the test;
- $N_{ai}$ : 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  $i$ ;
- $F_{ai}$ : 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.

## APPENDIX B. PROOF OF PROPOSITION 1

We first prove the following lemma.

**Lemma 1.** *If it exists, in any symmetric stage Nash equilibrium in which neither bank conducts creditworthiness 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  $s_i = (n_i = 0, N_{ai} < N, F_{ai})$ , then bank  $-i$  can strictly increase its profits by playing  $s'_{-i} = (n_{-i} = 0, N'_{a-i} = N, F_{a-i})$ , where the strategy  $s'_{-i}$  is to offer  $F'_{a-i} = F_{ai}$  to  $N_{ai}$  applicants (although these  $N_{ai}$  applicants might not be the same applicants that bank  $i$  is offering loans to), and offer  $X$  to the rest of them. Let  $F^*$  be the interest rate corresponding to zero profits in the loan market when there is no testing. Then

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

and

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

Assume bank  $i$  is playing  $s_i = (n_i = 0, N_{ai} < N, F_{ai})$ , with  $F_{ai} = (F_1, F_2, \dots, F_N)$ . Suppose  $F_j \geq F^*$  for  $j = 1, 2, \dots, N$  and assume there exist  $j$  and  $k$ , such that  $F_j \neq F_k$ , and, without loss of generality,  $F_k \geq F^*$ . Bank  $-i$  can strictly increase its profitability by playing  $s'_{-i} = (n_{-i} = 0, N'_{-i} = N, F'_{-i})$ , where  $F_{ai} = (F_1, \dots, F_{k-1}, F_k^-, F_{k+1}, \dots, F_N)$  and  $F_k^-$  is smaller than  $F_k$  by an infinitely small amount. Therefore, interest rates are bid down until each bank offers  $F^*$  to all the applicants.

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

## APPENDIX C. PROOF OF PROPOSITION 2

We first prove the following three lemmas.

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

The proof is similar to Lemma 1 and is omitted.

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

The proof is similar to that of Lemma 1 and is omitted.

**Lemma 4.** *If it exists, 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 1, we conclude that each bank offers loans to all non-tested applicants at the same interest rate. If there does not exist a feasible  $F$  such that the banks can make a non-negative profit by lending to non-tested applicants at  $F$ , we conclude that each bank offers loans to none of those non-tested applicants.<sup>30</sup>

*Proof Proposition 2.* The proof is by contradiction. If in equilibrium both banks conducting creditworthiness testing on all the applicants, from Lemma 2, both banks offer loans to all the applicants that pass the test, that is,  $N_\beta = N_g$ , where  $N_g$  denotes the number of applicants passing the test. Banks will make no loans to bad types found by testing, that is,  $N_\gamma = 0$ . Both banks use the creditworthiness 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  $E\pi \geq 0$ , that is, the participation constraints. For each realization of  $N_g$ , each bank expects to make loans to  $N_g/2$  applicants. Let  $p_k$  denote the probability of finding  $k$  good type applicants. Then:

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

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

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

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

For the case in which both banks conduct creditworthiness testing on a subset of the applicants, if the banks offer loans to 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.

#### APPENDIX D. FORMALIZATION OF THE REPEATED GAME

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

- (i) its own use of the creditworthiness test and the results;
- (ii) its own interest rate on the loan offered to applicants;
- (iii) its own choice of applicants that it lent to;
- (iv) its own and its competitor's loan portfolio size (number of loans made);
- (v) its own and its competitor's number of successful loans.

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

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

where  $D$  denotes the number of applicants that accepted the offer, and  $\chi$  denotes the number of successful borrowers;  $\alpha, \beta$ , and  $\gamma$  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

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

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:  $h_i^{T-1} = \{\alpha_{it}, K_{it}, \kappa_t\}_{t=0}^{T-1} \in H_i^{T-1}$ , where  $a_{it} = \{n_{it}, N_{ait}, N_{\beta it}, N_{\gamma it}, F_{ait}, F_{\beta it}, F_{\gamma it}\}$  is the action of bank  $i$  (by convention  $h_i^{-1} = \phi$ ). A (pure) strategy for bank  $i$  associates a schedule  $\sigma_{iT}(h_i^{T-1})$  with each  $T = 0, 1, \dots$  and  $\sigma_{iT} : H_i^{T-1} \rightarrow S$ , 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  $T = 0, 1, \dots$  and  $\sigma_{iT} : H^{T-1} \rightarrow S$ .

Given  $\lambda, p_g$ , and  $p_b$  (that is, nature's uncertainty), a strategy profile  $(\sigma_1, \sigma_2)$ , with  $\sigma_i = \{\sigma_{it}(\cdot)\}_{t=0}^\infty$ ,  $i = 1, 2$ , 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 pathwaywise pay-off for bank  $i$  is

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

where

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

## APPENDIX E. DEFINITION OF SPPE

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 *et al.*, 1994).

As shown by Abreu *et al.* (1990), any PPE pay-off for bank  $i$  can be factored into a first-period stage pay-off  $\pi_i$  (depending on the stage strategies of both banks) and a continuation pay-off 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 1.* An SPPE is a PPE 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 pay-off for the two banks are the same, but asymmetric play is allowed after the first period, for asymmetric realizations of loan portfolio size and loan performance.

**Lemma 5.** *In an SPPE, if on the equilibrium path, banks make offers to all loan applicants without creditworthiness test at an interest rate higher than  $F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g}$ , and the continuation pay-offs only depend on loan portfolio distribution  $(D_1, D_2)$ , then for any value of  $D$  we have*

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

*Proof.* Assume that there exists an SPPE with  $s = (n=0, N_\alpha = N, F_\alpha)$  played on the equilibrium path, where  $F_\alpha$  is a constant larger than  $F^* = \frac{1}{\lambda p_b + (1-\lambda)p_g}$ , and the continuation value function does not depend on  $(\chi_1, \chi_2)$ , which are the numbers of defaulted loans in banks' loan portfolios. To eliminate the incentive for a bank  $i$  to deviate to strategy  $s'(D) = (n=0, N_\alpha = D, F_\alpha^-)$  with  $0 \leq D \leq N$ , for any  $D \neq D'$ , we must have

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

which implies:

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

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

## APPENDIX F. DETAILS OF THE BOOTSTRAP

For each round of the bootstrap, the Significance Index (SI) 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 positive, 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.<sup>31</sup> 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 reject the null hypothesis and accept the alternative one.

The bootstrap algorithm is as follows:

**Step 1.** Run the OLS regression in  $H_0$ , for the two cases where  $y_{it} = LL_{it}$  or  $LR_{it}$ , and use the estimated coefficients,  $\alpha_{OLS}$ , to generate the residuals  $u_{it}^*$ .

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

31. Admittedly there is some arbitrariness in how the SI is constructed. However, we tried constructing the SI in a number of ways and found that the results are robust.

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

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

**Step 5.** Calculate the  $p$ -value of  $SI^*$ , that is,  $Pr(SI \geq SI^*)$ .

*Acknowledgements.* We thank Yacine Ait-Sahalia, Bernard Salanié, Kent Daniel, Steve Davis, Xavier Gabaix, Armando Gomes, Charles Kahn, Anil Kashyap, Richard Kihlstrom, Narayana Kocherlakota, Rob McMillan, George Mailath, Stewart Mayhew, Ben Polak, Eric Rosengren, Geert Rouwenhorst, José Scheinkman, Hyun Shin, Nick Souleles, Jeremy Stein, two anonymous referees, and seminar participants at Princeton, Yale, Duke, Chicago, Tsinghua, Renmin, the New York Federal Reserve Bank, the U.S. Securities and Exchange Commission, Moody's Investors Services and the NBER Conference on Capital Markets and the Economy for their comments and suggestions.

#### REFERENCES

- ABREU, D., PEARCE, D. and STACCHETTI, E. (1990), "Toward a Theory of Discounted Repeated Games with Imperfect Monitoring", *Econometrica*, **58** (5), 1041–63.
- ASEA, P. K. and BLOMBERG, S. B. (1998), "Lending Cycles", *Journal of Econometrics*, **83**, 89–128.
- ASGHARIAN, H. (2006), "A Comparative Analysis of the Ability of Mimicking Portfolios in Representing the Background Factors" (Working Paper, Lund University).
- ASHCRAFT, A. (2006), "New Evidence on the Lending Channel", *Journal of Money, Credit, and Banking*, **38** (3), 751–776.
- AUSUBEL, L. M. (1991), "The Failure of Competition in the Credit Card Market", *American Economic Review*, **81** (1), 50–81.
- BEATTY, A. L. and GRON, A. (2001), "Capital, Portfolio, and Growth: Bank Behavior Under Risk-Based Capital Guidelines", *Journal of Financial Services Research*, **20** (1), 5–31.
- BECK, T., DEMIRGUC-KUNT, A. and LEVINE, R. (2006), "Bank Concentration, Competition, and Crises: First Results", *Journal of Banking and Finance*, **30** (5), 1581–1603.
- BERGER, A. N. and UDELL, G. F. (1992), "Some Evidence on the Empirical Significance of Credit Rationing", *Journal of Political Economy*, **100** (5), 1047–1077.
- BERGER, A. N. and UDELL, G. F. (1994), "Do Risk-Based Capital Allocate Bank Credit and Cause a 'Credit Crunch' in the United States?", *Journal of Money, Credit and Banking*, **26** (3), 585–628.
- BERNANKE, B. S. and BLINDER, A. (1988), "Credit, Money, and Aggregate Demand", *American Economic Review*, **78**, 435–439.
- BERNANKE, B. S. and GERTLER, M. (1995), "Inside the Black Box: The Credit Channel of Monetary Policy", *Journal of Economic Perspectives*, **9** (4), 27–48.
- BERNANKE, B. S. and LOWN, C. S. (1991), "The Credit Crunch", *Brookings Papers on Economic Activity*, **2**, 204–39.
- BREEDEN, D. T., GIBBONS, M. R. and LITZENBERGER, R. H. (1989), "Empirical Tests of the Consumption-Oriented CAPM", *Journal of Finance*, **44**, 231–62.
- BRESNAHAN, T. (1989), "Empirical Studies of Industries with Market Power", in R. Schmalensee and R.D. Willing, eds., *Handbook of Industrial Organization*, Vol. 2 (New York: North Holland) 1011–57.
- BRINKMANN, E. J. and HORVITZ, P. M. (1995), "Risk-Based Capital Standards and the Credit Crunch", *Journal of Money, Credit & Banking*, **27** (3), 848–63.
- BROECKER, T. (1990), "Credit-Worthiness Tests and Interbank Competition", *Econometrica*, **58** (2), 429–52.
- CARHART, M. (1997), "Persistence in Mutual Fund Performance", *Journal of Finance*, **52**, 57–82.
- COCHRANE, J. (1999), "New Facts in Finance", *Economic Perspectives*, XXIII (3) (Federal Reserve Bank of Chicago).
- DELL'ARICCIA, G. and MARQUEZ, R. (2006), "Lending Booms and Lending Standards", *Journal of Finance*, **61** (5), 2511–2546.
- FAMA, E. and FRENCH, K. (1993), "Common Risk Factors in the Returns of Stocks and Bonds", *Journal of Financial Economics*, **33**, 3–56.
- FAMA, E. and FRENCH, K. (1996), "Multifactor Explanations for Asset Pricing Anomalies", *Journal of Finance*, **51**, 55–94.
- FUDENBERG, D., LEVINE, D. I. and MASKIN, E. (1994), "The Folk Theorem with Imperfect Public Information", *Econometrica*, **62** (5), 997–1039.
- FURFINE, C. (2001), "Bank Portfolio Allocation: The Impact of Capital Requirements, Regulatory Monitoring, and Economic Conditions", *Journal of Financial Services Research*, **20** (1), 33–56.
- GORTON, G. and WINTON, A. (2003), "Financial Intermediation", in G. Constantinides, M. Harris and R. Stulz, eds., *The Handbook of the Economics of Finance: Corporate Finance* (Elsevier Science) (NBER Working Paper # 8928).
- GREEN, E. J. and PORTER, R. H. (1984), "Noncooperative Collusion under Imperfect Price Information", *Econometrica*, **52** (1), 87–100.
- GROSS, D. and SOULELES, N. (2002), "An Empirical Analysis of Personal Bankruptcy and Delinquency", *Review of Financial Studies*, **15**, 319–347.



Group of Ten, "Report on Consolidation in the Financial Sector", January 25, 2001.

HALL, B. J. (1993), "How Has the Basle Accord Affected Bank Portfolios?" *Journal of the Japanese and International Economics*, **7**, 408–440.

HANCOCK, D. and WILCOX, J. A. (1994), "Bank Capital and the Credit Crunch: The Roles of Risk-Weighted and Unweighted Capital Regulations", *Journal of the American Real Estate & Urban Economics Association*, **22** (1), 59–94.

HANCOCK, D. and WILCOX, J. A. (1998), "The 'Credit Crunch' and the Availability of Credit to Small Business", *Journal of Banking and Finance*, **22**, 983–1014.

HAUBRICH, J. and WACHTEL, P. (1993), "Capital Requirements and Shifts in Commercial Bank Portfolios", *Economic Review* (Federal Reserve Bank of Cleveland), **29**, 2–15.

HOROWITZ, J. L. (2001), "The Bootstrap", *Handbook of Econometrics*, Vol. 5, J.J. Heckman and E.E. Leamer, eds., Elsevier Science B.V., Ch. **52**, 3159–3228.

JORDAN, J., PEEK, J. and ROSENGREN, E. (2002), "Credit Risk Modeling and the Cyclicity of Capital", Federal Reserve Bank of Boston, paper prepared for a conference on *Changes in Risk through Time Measurement and Policy Options*, BIS, Basel, March.

KEETON, W. R. (1994), "Causes of the Recent Increase in Bank Security Holdings", *Economic Review* (Federal Reserve Bank of Kansas City), **79** (2), 45–57.

LOWN, C. and MORGAN, D. P. (2005), "The Credit Cycle and the Business Cycles: New Findings Using the Survey of Senior Loan Officers", *Journal of Money, Credit & Banking* (forthcoming).

LOWN, C. and MORGAN, D. (2002), "Credit Effects in the Monetary Mechanism", *Economic Policy Review*, **8** (1), 217–235, Federal Reserve Bank of New York.

LOWN, C., MORGAN, D. and ROHATGI, S. (2000), "Listening to Loan Officers: The Impact of Commercial Credit Standards on Lending and Output", *Economic Policy Review*, **6** (2), 1–16, Federal Reserve Bank of New York.

PEEK, J. and ROSENGREN, E. (1995), "The Capital Crunch: Neither an Applicant Nor a Lender Be", *Journal of Money, Credit & Banking*, **27** (3), 625–638.

RAJAN, R. G. (1994), "Why Bank Credit Policies Fluctuate: A Theory and Some Evidence", *The Quarterly Journal of Economics*, **109** (2), 399–441.

REISS, P. and WOLAK, F. (2007), "Structural Econometric Modeling: Rationales and Examples from Industrial Organization", in J. J. Heckman and E. Leamer, eds., *Handbook of Econometrics*, **6A**, Chapter 64.

RUCKES, M. (2004), "Bank Competition and Credit Standards," *Review of Financial Studies*, **17**, 1073–1102.

SCHREFT, S. L. and OWENS, R. E. (1991), "Survey Evidence of Tighter Credit Conditions: What Does It Mean?", *Federal Reserve Bank of Richmond Economic Review*, **77** (2), 29–34.

WEINBERG, J. A. (1995), "Cycles in Lending Standards?", *Federal Reserve Bank of Richmond Economic Quarterly*, **81** (3), 1–18.

Copyright of *Review of Economic Studies* is the property of Blackwell Publishing Limited and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.