Screening Technology and Loan Portfolio Choice

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Abstract

We derives from a loan portfolio choice model the hypothesis that the inaccuracy level in the screening technology for a particular type of loan negatively affects the supply of that type of loan. This hypothesis is tested using three regression models, each of which includes the partial adjustment mechanism as well as incorporating one of the three different versions of expectations about inaccuracy: either adaptive expectations, Markov expectations, or perfect foresight. In all three regression models, this study finds that the U.S. banking industry data from 1987:1 to 2002:3 supports the hypothesis.

Keywords: Screening technology; Loan portfolio; Partial adjustment mechanism

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1. Introduction

The recent portfolio shifts in the US banking industry[1] have mainly been analyzed in terms of how banking regulations such as risk-based capital requirements have influenced them (for example Haubrich and Watchtel (1993), Berger and Udell (1994)). In contrast, this paper investigates the composition of the banking industry's loan portfolio by focusing on the screening technology[2] used in the loan approval process. We present some supportive evidence of the hypothesis that if the inaccuracy level of a screening technology for a particular type of loan increases, then the supply of that type of loan decreases, with other things remaining constant.

Our analysis focuses on variations in the proportion of commercial and industrial loans (C&I loans) in the banking industry's loan portfolio that is composed of C&I loans and consumer loans from 1987:1 to 2002:3. The reason that we examine these two types of risky loans is that the patterns of inaccuracy in the two kinds of screening technologies may differ across time since banks use standard credit scoring models in the consumer loan approval process but depend on in-house credit analysts in the C&I loan approval process.

We present a simple banking model that suggests our hypothesis. In our model, a representative bank chooses the minimal acceptable cut-off rating for each type of loan when the precision levels in screening technologies are exogenously given. We show that, under certain circumstances, if the inaccuracy level of a screening technology increases, then the cut-off rating for the associated type of loan also increases. This theoretical result can be intuitively explained as follows. Given the market interest rates for consumer loans, C&I loans, and safe assets, an individual risk-neutral bank with fixed funds would allocate its funds in the two types of loans and safe assets. In portfolio balance, the expected yield for each type of loan to marginal borrowers must be equal to the yield for safe assets. Suppose that the inaccuracy level in the screening technology for

[1] During 1987:1-2002:3, the proportion of commercial and industrial loans (C&I loans) to C&I loans and consumer loans for the banking industry has decreased from 64 percent in 1987 to a low of below 60 percent in 1995. Since 1995, the proportion has increased to 67 percent in 2000.
[2] A screening technology produces a credit score whose value is an estimated repayment probability of loan applicants.

consumer loans increases. Then the bank must increase the equilibrium cut-off rating used in its consumer loan approval process; otherwise it cannot maintain the expected yield from consumer loans to marginal borrowers.

To test the hypothesis and check the robustness of the result, we set up three regression models with the partial adjustment mechanism. The reason for the employment of the partial adjustment mechanism is to reflect the fact that banks cannot achieve the desired adjustment in their portfolio instantly. Each model also employs one of three different versions of a bank's formation of expectations about the inaccuracy: either adaptive expectations, Markov expectations, or perfect foresight. Adaptive expectations mean that banks adjust the current expectation about the inaccuracy of screening technologies based on the most recent error. Markov expectations mean that banks simply use the most recent known value of the inaccuracy to forecast the future value of the inaccuracy while perfect foresight means that banks correctly forecast the subsequent value of the inaccuracy. In all cases, the delinquency rate is adopted as a proxy variable for the inaccuracy in a screening technology. This adoption can be justified since we control for the risk involved in the two types of loans through the appropriate interest rates, the prime rate and the credit card loan interest rate.

The estimation results of the three regression models, which are derived from the same assumptions about a bank's behavior excluding the formation of expectations, are as follows. In all the three regression models, the US banking industry data supports our hypothesis by showing a significant negative relationship between the proportion of C&I loans and the inaccuracy in the associated screening technology

While we are not aware of any other research work addressing directly the question of how banks allocate their funds in various assets against the variation of accuracy of screening technology across time, our paper is related to the literature that explores the properties of banks' lending policies (for example Weinberg (1995), Keeton (1999). Lown *et al*. (2000), Baum *et al*. (2002)). Weinberg presents a model in which an aggregate shock is a main driving force of the fluctuation of credit standards. In his model, changes in lending standards occurs since borrowers' businesses are subject to exogenous shocks, which in turn determine the expected repayment probability of marginal borrowers. Hence the prediction of his model is that loan growth and falling credit standards occurs during good economic times.

Keeton argues that faster loan growth may tend to lead to higher loan losses by identifying the positive relationship between delinquency rates and lagged bank loans from a US bank data set on the industrial loans from 1982 to 1996. The basic argument behind Keeton's argument is that if loan growth increases due to an increase in loan supply, credit standards should fall and loan losses should eventually increase. However, Keeton does not pay attention to the effect of screening technology on bank loan supply. Similar in spirit to ours, Lown *et al.* investigate the value of the Senior Loan Officer Opinion Survey in predicting lending, and finds that the changes in commercial credit standards reported by loan officers are associated to aggregate loan growth. On the other hand, Baum *et al*. examine how macroeconomic uncertainty affects bank lending behavior by using a US bank panel data set from 1979:1 to 2000:4. They find that an increase in macroeconomic uncertainty causes a narrowing of the cross-sectional distribution of banks' loan-to-asset ratios.

Our work is also related to the literature that examines a banking equilibrium when a direct screening technology such as a credit worthiness test is available (for example Broecker (1990), Riordan (1993)). They extend the standard credit market model such as Stiglitz and Weiss (1981) by making available to his banks an exogenous and imperfect screening technology.

Section 2 describes a simple theoretical model. In Section 3, we set up the empirical models and provide the results. Section 4 presents concluding remarks.

2. Theoretical Analysis of the Bank's Loan Supply Decisions

Suppose a risk-neutral bank takes the market interest rates as given and allocates its given funds[3] into the three types of assets: consumer loans, industrial loans, and safe assets such as federal funds. Given the market interest rates, the bank determines the minimal acceptable credit score for each type of loan and will provide loans to loan applicants who are assigned to a higher credit score than the cut-off ratings.

The bank calculates the credit score for loan applicants by using the screening technology for consumer loans, $\tilde{s}_\alpha$ or the screening technology for industrial loans, $\tilde{k}_\beta$. For simplicity of analysis, we assume that the repayment probability of the loan for consumers, ρ and that for firms, μ are uniformly distributed over the open interval (0,1) respectively, and the two screening technologies are assumed to have the following specific characteristics.

$$\tilde{s}_\alpha : \begin{cases} \rho & \text{with probability } 1-\alpha \\ \text{uniformly distributed over } (0,1) & \text{with } \quad \alpha \end{cases},$$

$$\tilde{k}_\beta : \begin{cases} \mu & \text{with probability } 1-\beta \\ \text{uniformly distributed over } (0,1) & \text{with } \quad \beta \end{cases}.$$

The screening technology $\tilde{s}_\alpha$ means that for fixed $\alpha \in (0,1)$, when borrowers with the true repayment probability ρ are tested, the credit score s_α will be either ρ with probability $1-\alpha$ or uniformly distributed over (0,1) with α.[4] Therefore, the screening technology with the lower (higher) α is the more (less) accurate one; for example, a perfect screening technology $\tilde{s}_{\alpha=0}$ produces the credit score that reflects a loan applicant's true repayment probability perfectly.

This type of screening technology has the following desirable characteristics that we might require for a possible screening technology configuration: 1) For any $\alpha \in (0,1)$, the average repayment probability[5] $(1-\alpha)s_\alpha + 0.5\alpha$ of potential borrowers assigned to s_α

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[3] We assume that the size of funds is fixed in order to reflect that each bank has to satisfy the regulation on minimum leverage.

[4] All arguments related to $\tilde{s}_\alpha$ holds for $\tilde{k}_\beta$ since we assume that two types of loan applicants are characterized by the same distribution of the loan repayment probability.

[5] $(1-\alpha)s_\alpha + \alpha E(\tilde{\rho})$

is strictly increasing in s_α; 2) For any $s_\alpha \in (0.5,1)$, the average repayment probability $(1-\alpha)s_\alpha + 0.5\alpha$ of potential borrowers assigned to s_α is strictly decreasing in α; 3) For any $\alpha \in (0,1)$, the distribution of $\tilde{s}_\alpha$ is the same as the distribution of $\tilde{\rho}$; 4) The average repayment probability[6] $(1-\alpha)\frac{s_\alpha + 1}{2} + 0.5\alpha$ of potential borrowers assigned to a score higher than or equal to s_α is strictly decreasing in α.

Now we examine the bank's determination of the cut-off rating for consumer loans. Let s_α^* denote the solution to the optimal portfolio balance condition (1):

$$r = (1 + i_c)AVG(s_\alpha), \tag{1}$$

where r is one plus the interest rate for safe assets, $AVG(s_\alpha)$ is the average repayment probability of borrowers with score s_α, and i_c is the market interest rate for consumer loans.

Since r and i_c are exogenous to the banking firm and α depends on technology, s_α must be adjusted to satisfy portfolio equation (1). Therefore, s_α^* is the cut-off rating for consumer loans that the bank chooses in portfolio balance.

The cut-off rating s_α^* is a function of r, i_c and α. It is easy to verify that s_α^* is strictly increasing in α since $AVG(s_\alpha)$ is strictly decreasing in α for any $s_\alpha \in (0.5,1)$[7] and $AVG(s_\alpha)$ is strictly increasing in s_α for any $\alpha \in (0,1)$. It is also easy to verify that s_α^* is decreasing in i_c. Furthermore, if α decreases, the ratio of bad loans and total loans will decrease. This fact will serve to justify our selection of the delinquency rate as a proxy variable for the inaccuracy of screening technology.

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[6] $(1-\alpha)E(\tilde{\rho} \mid \rho \ge s_\alpha) + \alpha E(\tilde{\rho})$

[7] The case of $s_\alpha \le 0.5$ is roughly excluded based on actual practice within the banking industry.

3. Empirical Models and Estimation Results

The simple theoretical model illustrates the basis for our hypothesis about the relationship between screening technology and loan supply. To make the transition from the theoretical model to a compatible empirical model, we assume the partial adjustment mechanism in order to incorporate the fact that banks cannot achieve the desired portfolio instantly. Although the three regression equations to be considered here all make the assumption of a partial adjustment, they are distinguished by the different assumptions made about the formation of expectations about the inaccuracy: adaptive expectations, Markov expectations, or perfect foresight.

We use the aggregate quarterly data for the US banking industry from 1987:1 to 2002:3. Throughout the estimations, we use the delinquency rate[8] as a proxy variable for the inaccuracy in a screening technology. The detailed descriptions about data are provided in Table 1 and Figure 1.

3.1 The Partial Adjustment Portfolio Model

We assume a partial adjustment model to challenge portfolio decisions. To do so, we start by specifying the target portfolio as measured by the proportion of C&I loans to C&I and consumer loans as a function of anticipated screening technology and various interest rates.

In particular, we have

$$\left(\frac{L_{CI}}{L_{CI}+L_{CON}}\right)_t^* = \beta_0 + \beta_1 Inac_{CI,t}^* + \beta_2 Inac_{CON,t}^* + \beta_3 \left(\frac{PRime}{Creditrate}\right)_t , \qquad (2)$$

[8] Delinquent loans are defined in this paper as those 30 days or more overdue and still accruing interest as well as those in nonaccrual status.

where L_{CI} equals C&I loans, L_{CON} equals consumer loans, $(\frac{L_{CI}}{L_{CI}+L_{CON}})^*$ is the desired proportion of C&I loans in the loan portfolio, $Inac^*_{CI}$ is the expectation about the inaccuracy level in the screening technology for C&I loans, $Inac^*_{CON}$ is the expectation about the inaccuracy level in the screening technology for consumer loans, *PRime* denotes the prime rate, *Creditrate* denotes the 24-month credit card loan rate, and *t* is the time period. The equation (2) is based on the theoretical analysis that the loan supply is a function of i) the inaccuracy in the screening technology, and ii) the market loan interest rates. We use the ratio of the prime rate and the credit interest rate for convenience of estimation.

Given that loans are typically multi-period, portfolio adjustment can be represented by the partial adjustment mechanism,[9]

$$(\frac{L_{CI}}{L_{CI}+L_{CON}})_t - (\frac{L_{CI}}{L_{CI}+L_{CON}})_{t-1} = \delta \left[(\frac{L_{CI}}{L_{CI}+L_{CON}})^*_t - (\frac{L_{CI}}{L_{CI}+L_{CON}})_{t-1} \right], \tag{3}$$

where δ is the constant coefficient of adjustment, and has a value between 0 and 1. The equation (3) means that the actual change in the proportion of C&I loans in the banking industry's portfolio is only a fraction of the desired change.

3.2. The Adaptive Expectations Model

A critical feature of (2) is the role of expectations on the inaccuracy levels of various screening technologies on portfolio adjustments. One way of characterizing these expectations is adaptive. Thus we have

[9] This assumption is reasonable since banks adjust their portfolio mostly through newly placed loans because the second market for loans is not highly developed.

$$Inac^{*}_{CI,t} - Inac^{*}_{CI,t-1} = \lambda\,(Inac_{CI,t-1} - Inac^{*}_{CI,t-1}), \tag{4}$$

$$Inac^{*}_{CON,t} - Inac^{*}_{CON,t-1} = \lambda\,(Inac_{CON,t-1} - Inac^{*}_{CON,t-1}), \tag{5}$$

where λ is the adjustment factor, and has a value between 0 and 1. These formulae (4) and (5) state that the current expectation of $Inac$, $Inac^{*}_{t}$ equals last period's expectation, $Inac^{*}_{t-1}$, plus a term that adjusts this expectation in light of the most recent error.

Based on the equations (2), (3), (4) and (5), the regression equation system is obtained as

$$\begin{aligned} y_t - (1-\lambda)y_{t-1} &= \delta\lambda\beta_0 + \delta\lambda\beta_1 x_{1,t-1} + \delta\lambda\beta_2 x_{2,t-1} + \delta\beta_3[z_t - (1-\lambda)z_{t-1}] \\ &\quad + (1-\delta)[y_{t-1} - (1-\lambda)y_{t-2}] + \varepsilon_t, \\ \bar{y}_t &= y_t - (1-\lambda)y_{t-1}, \\ \bar{z}_t &= z_t - (1-\lambda)z_{t-1}, \end{aligned} \tag{6}$$

where $y_t = (\frac{L_{CI}}{L_{CI} + L_{CON}})_t$, $x_{1,t-1} = Inac_{CI,t-1}$, $x_{2,t-1} = Inac_{CON,t-1}$, and $z_t = (\frac{PRime}{Creditrate})_t$.

The specific derivation process is as follows. Let $y_t = (\frac{L_{CI}}{L_{CI} + L_{CON}})_t$, $x_{1,t-1} = Inac_{CI,t-1}$, $x_{2,t-1} = Inac_{CON,t-1}$, and $z_t = (\frac{PRime}{Creditrate})_t$. By plugging the equation (2), $y^{*}_t = \beta_0 + \beta_1 x^{*}_{1,t} + \beta_2 x^{*}_{2,t} + \beta_3 z_t$, into the equation (3), $y_t - y_{t-1} = \delta(y^{*}_t - y_{t-1})$, we have

$$y_t = \delta\beta_0 + \delta\beta_1 x^{*}_{1,t} + \delta\beta_2 x^{*}_{2,t} + \delta\beta_3 z_t + (1-\delta)y_{t-1}. \tag{7}$$

Now by multiplying the equation (7) throughout by (1-λ) and lagging it one period, we have

$$y_t = \delta\lambda\beta_0 + \delta\lambda\beta_1 x_{1,t-1} + \delta\lambda\beta_2 x_{2,t-1} + \delta\beta_3 z_t - \delta(1-\lambda)\beta_3 z_{t-1}$$
$$+ (1-\delta+1-\lambda) y_{t-1} - (1-\delta)(1-\lambda) y_{t-2}. \qquad (8)$$

After rearranging (8), we have the regression equation system (6).

In order to obtain estimation results,[10] we first get the estimate of λ from the equation (8): The coefficients of z_t and z_{t-1} determine the value of λ uniquely. Second, by using the estimate of λ, we generate necessary data and regress $\bar{y}_t$ on constant, $x_{1,t-1}$, $x_{2,t-1}$, $\bar{z}_t$, and $\bar{y}_{t-1}$. According to the theoretical analysis, we expect $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 > 0$.

From the equation (8), the adjustment factor in adaptive expectations, λ is estimated to be 0.37, which is reported in Table 2. The estimation results of the regression equation system (6) over the sample period are reported in Table 3. The estimate of β_1 is negative and significant; it suggests that an increase in the inaccuracy of the screening technology for C&I loans has a negative impact on the supply of C&I loans, because the proportion decreases only if the supply of C&I loans decreases, with consumer loans remaining constant. The estimate of β_2 is positive and significant; it also indicates that an increase in the inaccuracy of the screening technology for consumer loans has a negative impact on the supply of consumer loans, because the proportion increases only if the supply of consumer loans decreases, with C&I loans remaining constant. The estimate of β_3 is positive and significant; it suggests that if the C&I loan market interest rate increases, then the supply of C&I loans increases.

Since the equation provides a good fit to the data and the estimated values of β_1, β_2, and β_3 have expected signs and are significant, we can say that our hypothesis is supported by the data, when banks use adaptive expectations.

[10] Here, we employ a two-step estimation technique in Maddala (1977) p146. This is because λ is uniquely determined in the equation (8) while δ is over-determined.

3.3. The Markov Expectations Model

In this subsection, in order to test our hypothesis under another formation of expectations, we derive a regression model by replacing adaptive expectations with the assumption of Markov expectations,

$$Inac^{*}_{CI,t} = Inac_{CI,t-1}, \tag{9}$$

$$Inac^{*}_{CON,t} = Inac_{CON,t-1}. \tag{10}$$

The formulae (9) and (10) mean that banks simply use the most recent known values of the inaccuracies to forecast futures of the inaccuracies.

Based on the equations (2), (3), (9) and (10), the regression equation that incorporates Markov expectations is derived as (11):

$$\left(\frac{L_{CI}}{L_{CI}+L_{CON}}\right)_t = \delta\beta_0 + \delta\beta_1 Inac_{CI,t-1} + \delta\beta_2 Inac_{CON,t-1} + \delta\beta_3\left(\frac{PRime}{Creditrate}\right)_t + (1-\delta)\left(\frac{L_{CI}}{L_{CI}+L_{CON}}\right)_{t-1} + \varepsilon_t. \tag{11}$$

After plugging the equations (3), (9) and (10) into the equation (2), we have the regression equation (11).

The estimation results are reported in Table 4. Since the estimates of β_1, β_2, and β_3 have expected signs, the similar interpretations as in the partial adjustment/adaptive expectations model apply to the results of this Markov expectations model. The main difference between the results of the two models is that when we assume Markov expectations instead of adaptive expectations, the estimate of δ fairly decreases from 0.14 to 0.06 while $\overline{R}^2$ increases substantially.

3.4. The Perfect Foresight Model

In this subsection, we derive a regression equation by replacing the assumption of Markov expectations with the assumption of perfect foresight. By assuming that

$$Inac^{*}_{CI,t} = Inac_{CI,t+1}, \tag{12}$$

$$Inac^{*}_{CON,t} = Inac_{CON,t+1}, \tag{13}$$

we obtain the following regression equation:

$$\left(\frac{L_{CI}}{L_{CI}+L_{CON}}\right)_t = \delta\beta_0 + \delta\beta_1 Inac_{CI,t+1} + \delta\beta_2 Inac_{CON,t+1} + \delta\beta_3 \left(\frac{PRime}{Creditrate}\right)_t$$
$$+ (1-\delta)\left(\frac{L_{CI}}{L_{CI}+L_{CON}}\right)_{t-1} + \varepsilon_t \tag{14}$$

The only difference of the equation (14) from (11) is that the equation (14) uses lead variables instead of lag variables.

The estimation results are reported in Table 5. Since the estimates of β_1, β_2, and β_3 have expected signs, the similar interpretations as in Markov expectations model apply to the results of this perfect foresight model. The difference between the estimation results of those two models is that when we replace perfect foresight with Markov expectations, the estimate of δ somewhat decreases from 0.06 to 0.03.

4. Concluding Remarks

We analyzed the loan portfolio choice of a bank empirically and theoretically. In a simple theoretical model, we derived the hypothesis that if the inaccuracy level of a screening technology for a particular type of loan increases, then the supply of that type of loan decreases. In the empirical study, we constructed three regression models, i.e., partial adjustment/adaptive expectations, partial adjustment/Markov expectations, partial adjustment/perfect foresight, and we presented some supportive evidence for the hypothesis by using the US banking industry data from 1987:1 to 2002:3.

The main results of the three regression models are as follows. In the partial adjustment/adaptive expectations, the regression equation system fits the data very well, and the estimates of the coefficients of the inaccuracy variables have the expected signs and are also statistically significant. This result suggests the validity of our hypothesis in the partial adjustment/adaptive expectations framework.

Similarly, in the partial adjustment/Markov expectations model, our hypothesis is supported by the data; the regression model fits the data very well and the coefficients of the inaccuracy variables are estimated to have the expected signs and are also statistically significant. The main difference between those two models is that the estimated coefficient of the adjustment speed decreases fairly in the partial adjustment/Markov expectations model. Also, in the partial adjustment/perfect foresight model, our hypothesis is supported by the US bank data. The estimation result of the partial adjustment/perfect foresight model is similar to that of the partial adjustment/Markov expectations model except slightly lower adjustment speed. Regarding expectations, we do not find conclusive evidence that one kind of expectations fits the data better than the other kind.

Table 1. Descriptive Statistic for the Variables

Variable	Definition	Mean	Standard Deviation	Min.	Max.
$\frac{L_{CI}}{L_{CI}+L_{CON}}$	$\frac{\text{C\&I Loans*100}}{\text{C\&I Loans + Consumer Loans}}$	63.13	2.24	59.31	67.22
$Inac_{CI}$	Delinquency Rate for L_{CI}	3.55	1.67	1.59	6.38
$Inac_{CON}$	Delinquency Rate for L_{CON}	3.53	0.33	2.7	4.2
PRime	The Prime Rate	8.12	1.55	4.75	11.36
Creditrate	The 24-month Credit Card Rate	13.98	0.91	11.28	15.69

Notes: All data are about the US commercial banks from 1987:1 to 2002:3 and are collected from FRB Statistical Release. Consumer loans here do not include real estate loans.

Table 2. The Estimate of λ from the Equation (8)

Coefficients	Estimated Values
$\delta\lambda\beta_0$	0.0050 (0.55)
$\delta\lambda\beta_1$	-0.0007*** (–3.04)
$\delta\lambda\beta_2$	0.0059*** (3.84)
$\delta\beta_3$	0.0407*** (3.14)
$-\delta(1-\lambda)\beta_3$	-0.0258** (-2.03)
$(1-\delta+1-\lambda)$	1.3365*** (11.29)
$-(1-\delta)(1-\lambda)$	-0.3873*** (-3.38)

$\overline{R}^2 = 0.9890$, $D-W = 2.24$, $(1-\lambda) = 0.6339$, ( ): t-value

*** denotes significance at the 99 percent level
** denotes significance at the 95 percent level

Table 3. Coefficients of the Regression Equation System (6)

Coefficients	Estimated Values
$\delta\lambda\beta_0$	0.0108 (1.30)
$\delta\lambda\beta_1$	-0.0006*** (–2.68)
$\delta\lambda\beta_2$	0.0048*** (3.72)
$\delta\beta_3$	0.0331*** (4.00)
$1-\delta$	0.8576*** (19.96)

$\overline{R}^2 = 0.93$, $D-W = 2.51$, ( ): t-value

*** denotes significance at the 99 percent level

Table 4. Coefficients of the Regression Equation (11)

Coefficients	Estimated Values
$\delta\beta_0$	-0.0019 (0.19)
$\delta\beta_1$	-0.0011*** (–4.73)
$\delta\beta_2$	0.0072*** (5.66)
$\delta\beta_3$	0.0251*** (6.12)
$1-\delta$	0.9393*** (53.38)

$\overline{R}^2 = 0.9855$, $D-W = 1.1388$, ( ): t-value

*** denotes significance at the 99 percent level

Table 5. Coefficients of the Regression Equation (14)

Coefficients	Estimated Values
$\delta\beta_0$	-0.0062 (-0.58)
$\delta\beta_1$	-0.0012*** (-4.63)
$\delta\beta_2$	0.0061*** (4.68)
$\delta\beta_3$	0.0163*** (3.62)
$1-\delta$	0.9669*** (55.41)

$\overline{R}^2 = 0.9843$ $D-W =$ 1.0609, ( ): t-value

*** denotes significance at the 99 percent level

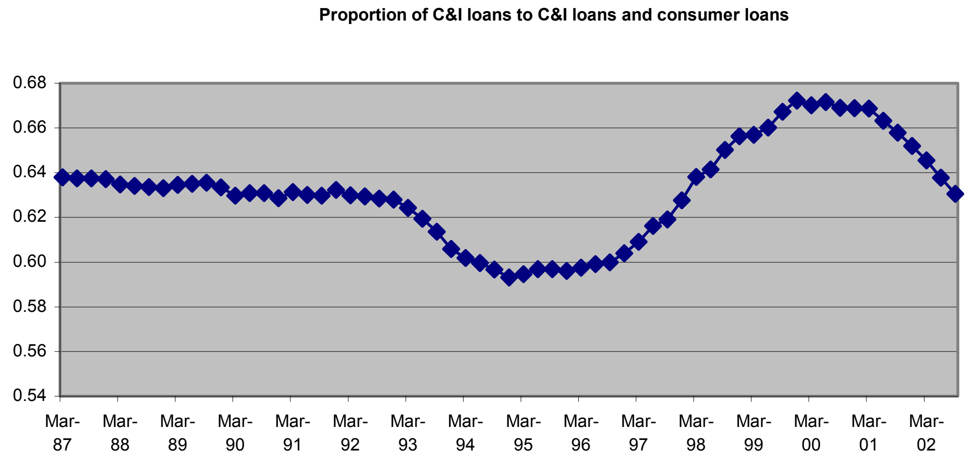

Figure 1. C&I Loans as a Percent of Total Loans

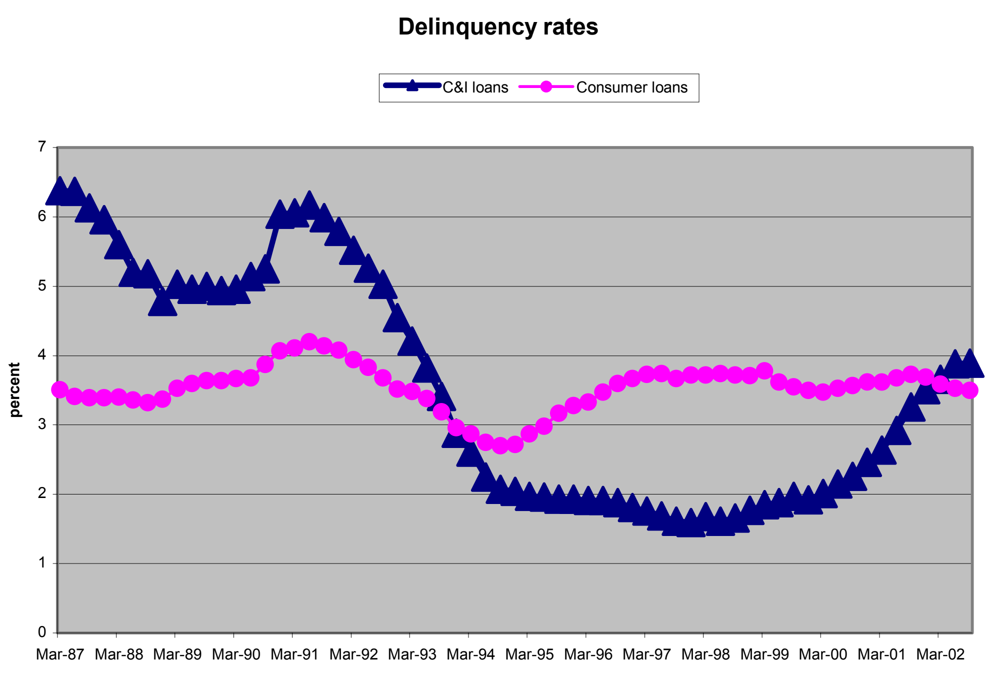

Figure 2. Delinquency Rates

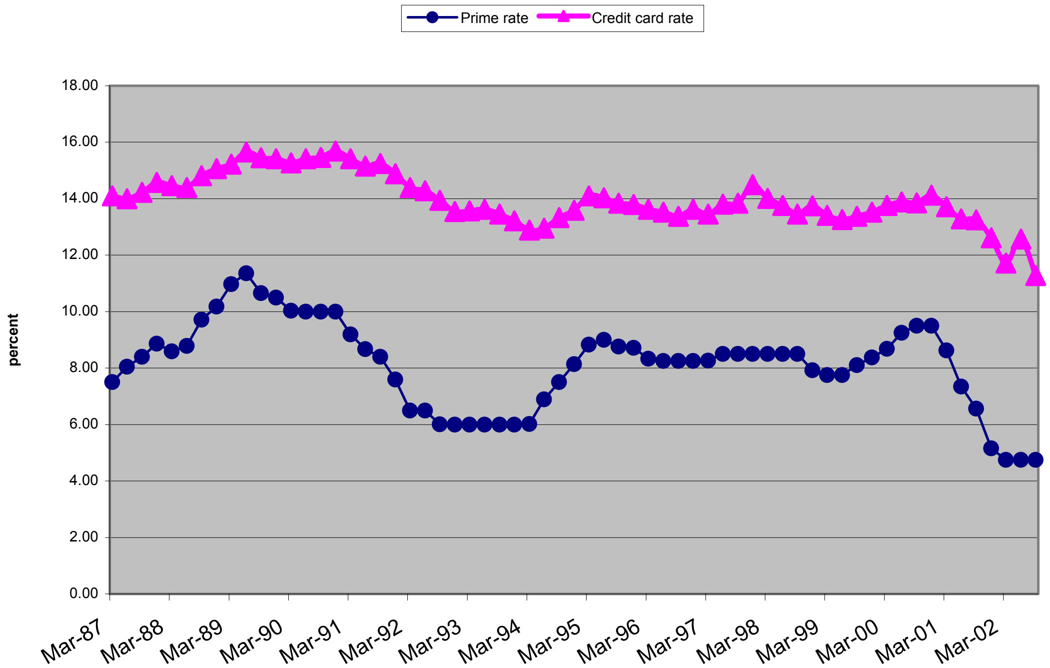

Figure 3. Interest Rates

References

Baum, C., M. Caglayan and N. Ozkan (2002), "The impact of macroeconomic uncertainty on bank lending behavior", mimeo

Berger, A. and G. Udell. (1994), "Did 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. and C. Lown. (1991), "The credit crunch", *Brookings papers on Economic Activity*, 0(2), 204-39.

Broecker, T. (1990), "Credit-worthiness tests and inter-bank competition", *Econometrica*, 58(2), 429-452.

Caouette, J., E. Altman and P. Narayanan. (1998), *Managing Credit Risk: the Next Great Financial Challenge*, John Wiley & Sons, Inc.

Haubrich, J. and P Wachtel. (1993), "Capital requirements and shifts in commercial bank portfolios", Federal Reserve Bank of Cleveland *Economic Review*, 29, 2-15.

Keeton, W. R. (1987), "Why do banks' loan losses differ?", Federal Reserve Bank of Kansas City, *Economic Review*, May, 3-21.

Keeton, W. R. (1999), "Does faster loan growth lead to higher loan losses?", Federal Reserve Bank of Kansas City, *Economic Review*, 2nd Quarter, 57-75.

Koehn, M. and A. Santomero. (1980), "Regulation of bank capital and portfolio risk", *Journal of Finance*, 35(5), 1235-44.

Lewis, E. (1992), *An Introduction to Credit Scoring*, Athena Press, 2nd edition.

Lown C., D. Morgan and S. Rohatgi (2000), "Listening to loan officers: the impact of commercial credit standards on lending and output", FRBNY *Economic Policy Review*, July, 1-16

Maddala, G. S. (1977), *Econometrics*, McGraw-Hill Book Company.

Rajan, R. G. (1994), “Why bank credit policies fluctuate: a theory and some evidence”, *Quarterly Journal of Economics*, 109(2), 399-441.

Rime, B. (2001), “Capital requirements and bank behavior: empirical evidence for Switzerland”, *Journal of Banking and Finance*, 25(4), 789-805.

Riordan, M. (1993), “Competition and bank performance: theoretical perspective” in C. Mayer and X. Vives, editors, *Capital Markets and Financial Intermediation*, 329-348, Cambridge University Press.

Sinkey, J. and M. Greenawalt. (1991), “Loan-loss experience and risk-taking behavior at large commercial banks”, *Journal of Financial Services Research*, 5(1), 43-59.

Stiglitz, J and A.Weiss. (1981), “Credit rationing in markets with imperfect information”, *American Economic Review*, 71, 393-410.

Weinberg, J. A. (1995), “Cycles in lending standards?”, Federal Reserve Bank of Richmond, *Economic Review*, 81(3), 1-18.