THE DIFFUSION OF FINANCIAL INNOVATIONS:
AN EXAMINATION OF THE ADOPTION OF SMALL BUSINESS CREDIT SCORING
BY LARGE BANKING ORGANIZATIONS

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March, 2001

Abstract

Financial innovation has been described as the "life blood of efficient and responsive capital markets." Yet, there have been few quantitative investigations of financial innovation and the <u>diffusion</u> of these new technologies. Of the latter, there have been <u>only three</u> prior quantitative studies, and all three used the same data set on ATMs!

This paper makes a significant contribution to the financial innovation literature by examining the diffusion of a recent important innovation of the 1990s: banks' use of credit scoring for small business lending. We examine the responses of 95 large banking organizations to a survey that asked whether they had adopted credit scoring for small business lending as of June 1997 (56 had done so) and, if they had adopted it, when they had done so. We estimate hazard and tobit models to explain the diffusion pattern of small business credit scoring models. Explanatory variables include several market, firm, and managerial factors of the banking organizations' under study.

The hazard model indicates that larger banking organizations innovated earlier, as did those located in the New York Federal Reserve district; both results are consistent with our expectations. The tobit model confirms these results and also finds that organizations with fewer separately chartered banks but more branches innovated earlier, which is consistent with theories stressing the importance of bank organizational form on lending style. Though the managerial variables' signs are consistent with our expectations, none yields significant results.

"One of the bedrocks of our financial system is financial innovation, the life blood of efficient and responsive capital markets." Van Horne (1985)

I. Introduction

It is widely recognized that innovation plays a crucial role in improving productivity. Equally important, however, is the rate at which innovations diffuse through an economy. Faster diffusion of innovations means a more immediate impact, and thus a higher social return on the initial investment.

There is general recognition of the particular importance of financial innovation (e.g., Silber 1975; Van Horne 1985; Miller 1986, 1992; Faulhaber and Baumol 1988; Campbell 1988, ch. 16; Siegel 1990; Finnerty 1992; and Merton 1992). However, the number of <u>quantitative</u> studies of financial innovation are relatively few and relatively recent (e.g., Garbade and Silber 1978; Hannan and McDowell 1984, 1987; Saloner and Shephard 1995; Lea 1996; Lerner 2000; Furst, et al. 2000; and Frame, et al. 2001).[1]

Further, we have been able to find only three quantitative studies that examine the diffusion process for financial innovations (Hannan and McDowell 1984, 1987; Saloner and Shepherd 1995), all using the same data on the introduction of automated teller machines.[2]

This paper will contribute to the empirical literature on the diffusion of financial innovations. Specifically, using a unique survey data set, we examine the introduction of credit scoring techniques for small business loan applications during the middle 1990s. This

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[1] This is in comparison with the much larger and much older set of quantitative studies that encompass innovation in manufacturing and agriculture. See Cohen and Levin (1989) for a review.

[2] Again, this is in contrast with a larger, older, and more varied set of diffusion studies that exist for manufacturing and agriculture. See, for example, Griliches (1957); Hagerstrand (1967); Mansfield (1968a, 1968b); Mansfield et al. (1977); Oster (1982); Thwaites (1982); Rees et al. (1984); Rose and Joskow (1990); and Baptista (2000).

survey yielded information for 99 large banking organizations, including whether they had

adopted credit scoring for small business lending by January 1998 and (if they had adopted)

when they first did so. We then relate this information to a number of market, firm, and

managerial factors in order to uncover the important characteristics driving technological

adoption decisions by large banking organizations. This is done by estimating a parametric

hazard function with time-varying covariates.[3] The benefit of using this approach is that we

can uncover the institutional factors that influence both the probability of and the rate of

small business credit scoring adoption. Allowing these factors to evolve through time (via

time-varying covariates) further enriches the model specification. We also employ tobit

analysis as an alternative means of capturing the relationship between the date of a bank's

adoption of credit scoring and the potential explanatory variables for its decision.

Our paper proceeds as follows. Section II provides background information about

small business credit scoring. Section III outlines our variables of interest. Section IV

discusses the data. Section V presents our statistical tests and results. Conclusions are

provided in Section VI.

II. Credit Scoring

Credit scoring is the process of assigning a single quantitative measure, or score, to a

potential borrower representing an estimate of the borrower's future loan performance

(Feldman, 1997). While credit scores have been used for some time in the underwriting of

consumer loans, this technology has only recently -- beginning in the 1990s -- been applied

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[3] The estimation of such hazard functions falls under the rubric of duration or survivor
analysis. See Kalbfleisch and Prentice (1980), Cox and Oakes (1984), and Kiefer (1988) for
an introduction to duration analysis.

to commercial credits. This is because commercial loans were thought to be too heterogeneous and documentation was not sufficiently standardized either within or across institutions (Rutherford 1994/1995). However, credit analysts ultimately determined that the personal credit history of small business owners is highly predictive of the loan repayment prospects of their businesses, especially for loans under $100,000.[4] Thus, personal information is obtained from a credit bureau and then augmented with basic business-specific data, so as to predict repayment. Eisenbeis (1996) presents an excellent overview of the history and application of credit scoring techniques to small business loan portfolios.

According to Feldman (1997), credit scoring will alter small business lending in three areas: (1) the interaction between borrowers and lenders; (2) loan pricing; and (3) credit availability. First, credit scoring allows lenders to underwrite and monitor loans without actually meeting the borrower. This development is in stark contrast to the perceived importance of a local bank-borrower relationship (Petersen and Rajan 1994; Berger and Udell 1995; and Cole 1998). In fact, because of scoring systems, borrowers can obtain unsecured credit from distant lenders through direct marketing channels. Second, the price of small business loans should decline -- especially for high credit quality borrowers that will no longer have to bear the cost of extensive underwriting. Also, increased competition -- resulting from small businesses having access to more lenders -- should further lower borrowing costs.[5] Third, credit scoring should increase credit availability for

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[4] Mester (1997) cites the use of information such as the applicant's monthly income, outstanding debt, financial assets, employment tenure, home ownership, and previous loan defaults or delinquencies.

[5] More lenders can compete for an individual borrower's loan because distance is less of a barrier and because the scoring technology may allow lenders that are not specialists at

small businesses. Better information about the repayment prospects of a small business applicant makes it more likely that a lender will price the loan based on expected risk, rather than denying the loan out of fear of charging too little. Moreover, the widespread use of credit scoring should increase future prospects for asset securitization by encouraging consistent underwriting standards.

Empirical evidence concerning Feldman's predictions has thus been far limited to the effect of credit scoring on small business credit availability. Frame et al. (2001) estimate that the use of credit scoring increases the portfolio share of small business loans by 8.4 percent for their sample of large banking organizations.

This paper examines a related, but new and different issue: what factors influence the probability and timing (i.e., the diffusion) of the adoption of this new technology by its "first movers": large banking organizations. To that end, the next section discusses a number of variables that we believe may affect the conditional probability of adopting small business credit scoring models.

III. Variables of Interest

We believe that a number of market, firm, and managerial factors may have influenced the diffusion of credit scoring technology for small business loans. Most importantly, the rate of diffusion should be related to the expected benefits (profitability) of adopting the new technology. Indeed, various theoretical models of this exist (Davies, 1979; Reinganum, 1981a,b; Fudenberg and Tirole, 1985; and Karshenas and Stoneman, 1993). However, in the spirit of agency theory, we also believe that variations in the risk

borrower evaluation to enter the lending business.

preferences and ability (foresight) of firm managers could also influence adoption decisions. We discuss each of the covariates included in our analysis below.

A. Market Variables

The relative competitiveness of the marketplace may influence technological adoption decisions. However, two competing theories exist. On the one hand, Schumpeter (1950) contends that large firms with market power are most likely to advance industrial technology because of their superior access to capital, the ability to pool risks, and economies of scale. On the other hand, Scherer (1984) suggests that small firms are relatively more likely to innovate than are large firms, because of standard competitive motives. Generally, as an empirical matter, Cohen and Levin (1989) report that if a relationship between market concentration and innovation exists, it is "fragile" and likely to be economically unimportant. Nevertheless, in the area of financial services innovation, Hannan and McDowell (1984) provide empirical evidence -- based on the adoption of automated teller machines by banks – that is consistent with Schumpeter's theory. Accordingly, to account for the possible relationship between market concentration and financial innovation, we include an average Herfindahl-Hirschman Index (HHI) across all the local geographic markets in which the subsidiary banks operate weighted by their total assets in each market.[6]

There is considerable research suggesting that technological adoption varies geographically (Hagerstrand, 1967; Thwaites, 1982; and Rees et al. 1984). Baptista (2000) suggests that these regional differences in diffusion rates result from the geographical

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[6] Elliehausen and Wolken (1990) provide empirical support for the notion that small business lending markets tend to be local.

clustering of innovators. Similarly, we posit that the geographic distribution of individuals qualified to develop and maintain sophisticated econometric credit scoring models may be concentrated, specifically in New York and San Francisco. This conjecture is based on the tremendous demand by Wall Street firms for so-called "quants" and the fact that the largest vendor of credit scoring models (Fair Issac & Company) is based in the San Francisco area. To account for this, we include dummy variables indicating whether the banking organization is located in the New York (NEWYORK) or San Francisco (SANFRAN) Federal Reserve districts.

B. Firm Variables

Studies have found that larger firms are likely to adopt new technologies before smaller firms (Mansfield, 1968a, 1968b, 1977; Hannan and McDowell, 1984; Rose and Joskow, 1990). This is likely due to the fact that the cost of a new technology can be spread across a larger number of units of output. To account for this, we include the natural logarithm of total domestic banking assets (LNASSETS).

We believe that banking organizations that are more focused on small business lending are more apt to adopt credit scoring. Because credit scoring serves objectively to measure and rank the riskiness of borrowers, financial institutions are better able to manage credit risk and price loans accordingly. Thus, for those institutions especially dependent on earnings from small business lending, credit scoring should be more valuable. As a result we include the ratio of small loans (under $100,000) to businesses to total domestic banking assets (SBLRATIO).

The underlying structure of the banking organization may also influence the technology adoption decision. For this reason, we include both the number of subsidiary banks (NBANKS) and the number of branches (BRANCHES) in our model. A larger number of subsidiary banks may indicate a decentralized organizational structure that emphasizes more localized control over lending decisions. We would expect that these types of banking organizations are less likely to engage in credit scoring. On the other hand, we see banking organizations with expansive branch networks as more likely to use an automated approach to underwriting loans.

The profitability of an institution may influence its propensity to adopt new technologies. Hannan and McDowell (1984) suggest that this might stem from a liquidity constraint; less profitable firms are less able to invest in new technologies.[7] For this reason, we include return on equity (ROE), or net income as a percent of total equity capital, as a measure of profitability.

Identifying organizational willingness to implement new programs or technologies is difficult. While this may come from chief executives (see below), it may also be related to a firm's corporate culture. For example, Furst, et al. (2000) find that the probability of federally chartered commercial banks to adopt internet banking is positively related to their reliance on non-interest income. That is, "fee income" may act as a proxy for the

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[7] This was one of Schumpeter's (1950) arguments in favor of monopoly (with its larger profit flow) as a superior market structure for encouraging innovation. In the language of more modern economics, the asymmetric information problems surrounding a firm's attracting "outside" finance for an investment are even greater when the investment involves uncertain new technologies that may have little liquidation value. Thus a firm with a greater capability for internal finance (from greater profits) will have an advantage with respect to investing in new technologies.

aggressiveness of the bank's business strategy. Accordingly, we include the ratio of non-interest income to net operating revenue (NIINCOME).

C. CEO Variables

Lastly, personal characteristics of each banking organization's chief executive officer (CEO) may influence the adoption decision. This focus on management has previously been explored in the technology diffusion literature, primarily by Mansfield (1968a, 1968b, 1977). The two CEO variables we have selected are tenure and education.[8] First, the length of time that an executive has been with an organization (CEOTEN) may influence decision-making in opposing ways. On one hand, the longer a CEO has been with a firm, the more he/she knows about its labor resources and how to mobilize them. On the other hand, new managers may be more likely to "shake-up" an organization and try new approaches – especially in formerly protected industries like banking. Second, we posit that executives with additional education beyond their college degrees will be more inclined to adopt new technologies. The dummy variable ADVDEG accounts for this by taking a value of one for CEOs with graduate degrees.

III.   Data

The data used in this study come from three sources. First, we have data recording the month and year that a sample of large banking organizations first used small business credit scoring. This information was obtained from a survey of the 200 largest U.S. banking

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[8] In previous efforts, we had also included CEO age in our analysis. Because it was generally found to be unimportant (and correlated with CEO tenure), we have dropped it here.

organizations (as of June 1997) conducted by the Federal Reserve Bank of Atlanta in January 1998. Ninety-nine institutions responded to the survey in which (among other things) respondents were asked whether their institution credit scored small business loans and, if so, when it was first implemented. See Frame et al. (2001) for a complete discussion of the survey questions and results.

Second, we use several items reported on the commercial bank Call Reports (and aggregated to the holding company level). This information was obtained from the Wharton Financial Institutions Center (which, in turn, obtained the data from the Federal Reserve Board). Since information about banks' small business lending activities is only collected on the mid-year Call Report (and only since 1993), this is how we organize our analysis. As a result, we focus on annual, mid-year observations for each large banking organization between 1993-1997.

Lastly, we collected data on the personal characteristics of the chief executive officers (CEOs) of each large banking organization that responded to our survey. Specifically, information on CEO tenure and education was obtained primarily from the Forbes magazine "500" lists.[9] Because CEO information was unavailable for four institutions (all foreign-owned), our analysis ultimately focuses on a total of 95 large banking organizations.

Table 1 provides the descriptive statistics for our sample, as of June 1997. Of the 95 large banking organizations in our sample, 55 (58 percent) had adopted credit scoring for small business lending by June 1997. Of those that did adopt, nine had adopted before

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[9] This biographical information can be found on the Forbes website (www.forbes.com). For information on CEOs who were not in those lists, we turned to various "Who's Who" directories and news stories in the American Banker.

1995, while the remainder adopted during the last few years of our sample period. On average, the large banking organizations in our sample had 1.7 percent of their portfolios devoted to small business lending. These institutions were quite profitable (an average return on equity of almost 16 percent) and earned about 30 percent of their revenues from fees. These banking organizations averaged seven subsidiary banks and 367 bank branches. Almost 13 percent of the institutions were located in the San Francisco Federal Reserve district, while over seven percent were in the New York district. On average, chief executives in the sample organizations had been in their positions for over nine years, and about half (47 percent) had advanced degrees.

Table 2 provides the simple correlation matrix among the variables listed in Table 1. We have also included ADOPT, which is a dummy variable indicating whether the banking organization had adopted the innovation by June 1997, and YEARS, which is an integer equal to the number of years that the institution has used credit scoring. For example, YEARS is equal to one if the banking organization had used credit scoring for 1-12 months as of June 1997.

As can be seen, ADOPT is positively and statistically significantly related to YEARS, LNASSETS, and BRANCHES, while negatively related to SBLRATIO. YEARS is positively and statistically significantly associated with LNASSETS, BRANCHES, NEWYORK, and ADVDEG. These last four results are all consistent with the expectations discussed above.

Among the independent variables, the following interesting correlation coefficients are worth mentioning. First, SBLRATIO has significant negative associations with LNASSETS, BRANCHES, and NEW YORK and significant positive associations with

HHI and CEOTEN. Thus, small business lending tends to be relatively less important at larger banks, banks with more branches, and banks located in the New York Federal Reserve district. Also, small business lending is more important in more concentrated markets (which tend to be smaller, less urban, and populated with smaller banks) and where the CEO has been with the bank longer (which tends to be associated with smaller banks). Second, LNASSETS has significant positive associations with BANKS, BRANCHES, ADVDEG, and NIINCOME and a significant negative association with HHI. In other words, larger banking organizations tend to have more constituent banks and branches (as expected), to have a CEO with an advanced degree, and to have higher relative non-interest income (as expected), while they tend to operate in less concentrated (larger, urban) markets.

We now turn to the detailed tests of our hypotheses.

V. Tests and Results

To examine the determinants of the likelihood and timing of small business credit scoring adoption we estimate two different statistical models, a hazard and a tobit. The hazard model is of primary interest because it utilizes information over the entire 1993-1997 time frame. The tobit model, which relies on cross-sectional data from 1997 for the explanatory variables, provides a supplement to the results of the hazard model.[10]

The hazard model allows us to determine simultaneously the institutional factors that influence both the probability of and the rate of small business credit scoring adoption. This

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[10] We used the 1997 data because it represents the realizations of how our sample institutions evolved over the 1993-1997 period. Using the 1993 data, by contrast, may not be as good a predictor of future activity because future business decisions are unobserved or otherwise unaccounted for.

approach views the adoption of small business credit scoring as the "hazard" and therefore only includes observations during which these models are not being used by the institution. The dependent variable in this model is the natural logarithm of the number of years until adoption occurs. A detailed description of hazard, or duration, analysis is provided below.

The dependent variable in the tobit model is the number of years that the banking organization had been using credit scoring as of June 1997 (YEARS). Thus, large banking organizations that had not adopted credit scoring for their small business loan portfolios are censored and are coded with zero. The estimated coefficients in the tobit model tell us what variables influence the timing of credit scoring adoption.

Denoting Y as the relevant dependent variable (and suppressing the institution and time subscripts), the following relationship can be denoted for both statistical models:

(1) $Y = f$ (SBLRATIO, LNASSETS, BANKS, BRANCHES, HHI, SANFRAN, NEWYORK,   ADVDEG, CEOTEN, ROE, NIINCOME).

Both models are estimated by maximum likelihood using LIMDEP, Version 7.0.

A. Hazard Model

To examine both the likelihood and rate of small business credit scoring adoption, we estimate a hazard model. Using standard duration analysis, we estimate a hazard rate at which firms adopt small business credit scoring conditional on both time and the market, firm, and CEO characteristics outlined in Section IV. To this end, we begin by providing an overview of duration analysis and then turn to the results yielded by this procedure.

1. Overview

The variable of interest in the analysis of duration is the length of time, T, that elapses from the beginning of some event until its end or until measurement is taken (Greene, 1997). In our case, we are interested in the length of time that elapses before large banking organizations adopt credit scoring for underwriting small business loans. We then estimate a hazard rate, or the probability of an adoption in each year given that the institution has not introduced credit scoring by that time.

Following Kiefer (1988), we describe a cumulative probability distribution as:

(2) $F(T) = Prob(T \leq t)$,

or the probability that the non-negative random variable T is less than some value t. By definition, this cumulative probability can also be described in terms of a probability density function:

(3) $f(t) = dF(t)/dt = F'(t)$.

Alternatively, one can specify a survival function,

(4) $S(t) = 1 - F(T) = Prob(T \geq t)$.

Given these definitions (2)-(4), we can then present a hazard function or the probability that an institution will adopt small business credit scoring at time T, given that it has not done so by that time:

(5) $\lambda(t) = f(t) / S(t)$.

Furthermore, by substituting (3) and (4) into (5) it can also be shown that:

(6) $\lambda(t) = -d \ln S(t) / dt$.

The hazard function may also be related to explanatory variables:

(7) $\lambda(t) = f(X_t\beta)$

where X is a matrix of variables influencing the hazard rate and β is a vector of regression

coefficients. The variables in X may also be updated through time reflecting what the duration literature refers to as time-varying covariates.

Assuming a particular underlying probability distribution for λ implies a likelihood function that can be maximized to generate parameter estimates for β and any other variables dictated by the distribution of λ. However, as noted by Greene (1997), censoring is a pervasive and usually unavoidable problem in the analysis of duration data. As a result, the general form of the log-likelihood function is:

$$(8) \qquad L(\theta) = \sum_{i=1}^{n} d_i \ln f(t,\theta) + \sum_{i=1}^{n} (1-d_i) \ln S(t,\theta)$$

where the indicator d_i equals one for an uncensored observation and zero otherwise.

For our sample of 95 large U.S. banking organizations, we observe credit scoring adoption decisions annually over the 1993-1997 period. Those institutions that had not adopted credit scoring by mid-year 1997 are "right censored" and therefore have no "failure times." We estimate this model, including time-varying covariates, assuming a Weibull distribution.[11] The Weibull distribution is selected because it is consistent with the overall-increasing rate of credit scoring adoption observed during the sample period.

2.   Results

Table 3 presents the estimation results for the parametric hazard function assuming a Weibull process for the hazard rates.[12] We find that only two of our variables of interest are

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[11] Kiefer (1988) and Greene (1997) both present the survivor, probability distribution, and hazard functions for the Weibull and other distributions.

[12] Note that we must be careful in interpreting the parameters: a negative coefficient means a negative effect on duration and therefore a positive effect on adoption speed.

statistically related to the rate of small business credit scoring adoption: LNASSETS and

NEWYORK. Specifically, the model indicates that both variables are negatively related to

the probability of <u>not</u> adopting small business credit scoring through the sample period.

Equivalently, larger banking organizations and those headquartered in the New York

Federal Reserve district tended to adopt the new technology sooner. As noted above, these

findings are consistent with the presence of increasing returns to technology adoption and

the geographic clustering of adopters. There is little discernable relationship between the

rate of credit scoring adoption and any of our other market, firm, or CEO variables. As

measured by a log-likelihood ratio (chi-square) test, the model easily rejects the null

hypothesis of no relationship at a 1 percent level.

Next, we estimate a somewhat similar tobit model to supplement our results.

B. Tobit Model

Table 4 displays the results for the tobit analysis, in which YEARS is the dependent

variable. Consistent with the hazard model results, we find a positive and statistically

significant coefficient on LNASSETS. This indicates that, as predicted, the larger

institutions adopted credit scoring before the smaller ones. Second, we find that the

coefficient on NEWYORK is positive and marginally significant (at the 11 percent level).

This finding is consistent with the literature on the geographic diffusion of new

technologies. We also find that YEARS is negatively related to the number of subsidiary

banks and positively related to the number of bank branches.[13] However, the coefficient on

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[13] This result is consistent with results reported by Frame et al. (2001) for the probability
of having adopted small business credit scoring.

BRANCHES is only marginally significant (14 percent level). These results support the conjecture that bank organizational structure influences lending style.

One additional note about the tobit model is that the coefficient on ADVDEG is positive, but only modestly significant (at the 17 percent level). Further, going back to the simple correlation coefficients (Table 2), there was a significant positive association between YEARS and ADVDEG. We suspect that since ADVDEG is positively correlated with LNASSETS, and the latter variable is significant in the tobit regression, it is possible that the positive influence of ADVDEG has been subsumed within LNASSETS. As was true for the hazard model, a log-likelihood (chi-square) test easily allows us to reject the null hypothesis at the 1 percent level.

VI. Conclusions

In this paper we have tested a diffusion model of technology adoption for the financial services industry. Specifically, we examine the characteristics of the early adopters of small business credit scoring using two statistical tests. Using both hazard and tobit analysis, we find that larger banking organizations and those located in the New York Federal Reserve district adopted small business credit scoring before their peers. The former finding is consistent with the presence of economies of scale for technology adoption, and the latter with theories of geography-dependent innovation diffusion. The tobit analysis also indicates that the likelihood of adopting small business credit scoring was positively related to the size of the branching network and negatively related to the number of bank charters. This is consistent with theories concerning the relationship between bank

organizational form and lending style. Various CEO characteristics did not have significant explanatory power in our statistical tests.

Further work can surely be done to extend these analyses. For example, it would certainly be useful to know the extent to which small business credit scoring pervades the industry today. It would also be interesting to see if our findings are consistent for other financial innovations – particularly on the credit side of the banking business. Since financial innovation is "the life blood" of the financial sector, further efforts to understand the diffusion of this vital ingredient through the sector are surely warranted.

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Table 1
Sample Statistics for 95 Large U.S. Banking Organizations
(Data as of June 30, 1997)

Number of Banking Organizations that had adopted credit scoring for small business lending by June 1997: 55

       Number that adopted in 1992: 1
       Number that adopted in 1993: 2
       Number that adopted in 1994: 6
       Number that adopted in 1995: 9
       Number that adopted in 1996: 28
       Number that adopted in 1997: 9

	Average	Std. Deviation	Minimum	Maximum
SBLRATIO	0.0167	0.0100	0.0015	0.0510
LNASSETS	9.3859	1.2660	7.2364	12.3351
BANKS	6.9053	8.6234	1.0000	38.0000
BRANCHES	367.3789	476.5632	13.0000	2617.0000
HHI	0.1880	0.0602	0.0709	0.5005
SANFRAN	0.1263	0.3340	0.0000	1.0000
NEWYORK	0.0737	0.2626	0.0000	1.0000
ADVDEG	0.4737	0.5020	0.0000	1.0000
CEOTEN	9.1789	7.8753	0.0000	40.0000
ROE	0.1588	0.3291	0.0728	0.2526
NIINCOME	0.2984	0.0997	0.0951	0.6405

Table 2
Simple Correlation Coefficients

	ADOPT	YEARS	SBLRATIO	LNASSETS	BANKS	BRANCHES	HHI	SF	NY	ADVDEG	CEOTN	ROE	NIINC
ADOPT	1.00												
YEARS	0.75***	1.00											
SBLRATIO	-0.22**	-0.16	1.00										
LNASSETS	0.46***	0.51***	-0.46***	1.00									
BANKS	-0.05	-0.07	0.04	0.27***	1.00								
BRANCHES	0.38***	0.50***	-0.25**	0.80***	0.34***	1.00							
HHI	-0.13	-0.10	0.40***	-0.21**	-0.06	-0.09	1.00						
SF	0.07	-0.01	-0.03	0.09	-0.06	0.14	0.10	1.00					
NY	0.16	0.19*	-0.21**	0.12	-0.14	-0.03	-0.03	-0.11	1.00				
ADVDEG	0.17	0.25**	-0.08	0.35***	0.10	0.22**	-0.02	-0.04	-0.03	1.00			
CEOTN	-0.13	-0.06	0.22**	-0.16	0.13	-0.07	0.10	-0.03	0.03	-0.07	1.00		
ROE	-0.7	-0.12	-0.12	0.02	0.09	-0.13	-0.09	-0.14	0.21**	0.18*	-0.13	1.00	
NIINC	0.07	0.13	-0.19*	0.18*	0.18*	0.28***	-0.04	-0.08	-0.13	0.25**	-0.12	0.14	1.00

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Table 3
Hazard Model Estimates of the Length of Time to Adoption
Of Small Business Credit Scoring
Dependent Variable: ln(TIME)

	Coefficient	T-Statistic	Probability
Constant	3.1627***	3.320	0.0009
SBLRATIO	3.0062	0.376	0.7068
LNASSETS	-0.1968*	-1.874	0.0609
BANKS	0.0022	0.361	0.7179
BRANCHES	-0.0002	-0.742	0.4580
HHI	0.0006	0.001	0.9996
SANFRAN	0.0702	0.326	0.7445
NEWYORK	-0.3654*	-1.703	0.0886
ADVDEG	-0.0004	-0.003	0.9973
CEOTEN	-0.0026	-0.287	0.7744
ROE	0.2848	0.186	0.8523
NIINCOME	1.0012	1.323	0.1858
$\lambda = \exp(-\beta'X)$	0.1940		
$P = 1/\sigma$	2.6657		
Median	4.4923		

Log-likelihood = -136.0775; chi-square = 35.0242
* Statistically significant at the 10 percent level.
** Statistically significant at the 5 percent level.
*** Statistically significant at the 1 percent level.

Table 4
Tobit Estimates of Variables Influencing the Rate of Adopting
Small Business Credit Scoring
Dependent Variable: YEARS
(June 30, 1997 Data)

	Coefficient	T-Statistic	Probability
Constant	-4.3946	-1.533	0.1252
SBLRATIO	26.9891	1.123	0.2616
LNASSETS	0.7268**	2.419	0.0156
BANKS	-0.0639***	-2.663	0.0077
BRANCHES	0.0010	1.497	0.1343
HHI	-3.3464	-0.916	0.3595
SANFRAN	-0.4576	-0.814	0.4155
NEWYORK	1.1691	1.625	0.1042
ADVDEG	0.5378	1.393	0.1636
CEOTEN	-0.0075	-0.298	0.7657
ROE	-8.0597	-1.312	0.1895
NIINCOME	-1.6310	-0.751	0.4527

Log likelihood = -151.8044; chi-square = 46.1456
* Statistically significant at the 10 percent level.
** Statistically significant at the 5 percent level.
*** Statistically significant at the 1 percent level.