VI. Credit Scoring And Securitization of Small Business Loans

Credit Scoring and Small Business Lending in Low- and Moderate-income Communities

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Using survey data from the largest 200 U.S. commercial banks originally taken and used for the paper, "The Effect of Credit Scoring on Small Business Lending" by W. Scott Frame, Aruna Srinivasan, and Lynn Woosley (1998), this paper explores small business lending activity of banks that use automated underwriting techniques (i.e., credit scoring) in low- and moderate-income communities. First, by using statistics controlling for small business activity and comparing the lending activities of banks that used credit scoring in small business lending and those that do not, we do not find an indication that credit scoring banks have restricted credit to low- and moderate-income areas relative to non-scoring banks. Then, by controlling for various institution-specific and community-specific variables, we find that credit scoring has a significantly positive effect on the amount of small business credit extended in low-income communities and a mixed effect in moderate-income communities. Our findings do not support an argument that automated procedures in the small business lending process restricts the amount of credit extended to small businesses located in low- and moderate-income communities.

Small Business Lending

Small Business Lending—General

Small business credit markets differ markedly in some ways from those for larger businesses. Recent theories of small business lending have centered on the information flows between small business borrowers and lenders (Nakamura, 1993). Both asymmetric information problems and monitoring costs tend to be larger for creditors of small businesses than those of large businesses, since securities rating agencies and the financial press are unlikely to devote resources to monitoring

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small firms. Small business lending appears to be more relationship-based than other commercial lending (Elliehausen and Wolken, 1990; Peterson and Rajan, 1994; Berger and Udell, 1995; Berger and Udell, 1996). As a result, small businesses, lacking access to the public capital markets, have traditionally relied on bank and nonbank financial institutions for funds. Likewise, banks have historically invested substantial resources into small business credit markets.

In recent years, however, small businesses have relied less on traditional bank loans for funding. The 1997 Arthur Andersen / National Small Business United Survey revealed that only 38 percent of respondents rely on bank loans for their financing needs, down from 49 percent in 1993. According to the same survey, small businesses increasingly tend to use credit card financing as their primary source of capital.[1]

Changes in the banking industry have driven significant research into *who* lends to small businesses. The banking industry has experienced significant consolidation, resulting in larger institutions. Although the evidence concerning small business lending by large banks is mixed, these institutions may invest a smaller proportion of their resources in small business loans. One early study showed that banks owned by multibank holding companies or out-of-state holding companies tended to lend a smaller proportion of their funds to small businesses than do independent banks (Keeton, 1995). Another (Peek and Rosengren, 1995) indicated that, in a majority of cases, large acquirers did not maintain the small business loan portfolios of their small target banks. More recently, empirical evidence indicates that small business lending is growing more rapidly at small banks than at large banks, and that small acquirers are more likely than large acquirers to expand small business lending (Peek and Rosengren, 1998a; Zardkoohi and Kolari, 1997; Keeton, 1996). Lastly, Peek and Rosengren (1998b) found that, although approximately half of acquirers increased and half decreased the share of small business loans in their portfolios following a merger, a tendency remained for large acquirers to decrease small business lending.

Conversely, Whalen (1995) found that out-of-state bank holding companies compared favorably with both independent banks and in-state bank holding companies in small business loan volume and pricing. Strahan and Weston (1996) found that the pre- and pro-forma ratios of small business loans to total assets for merging institutions increased from 1993 to 1995. Using data from the National Survey of Small Business Finances, Jayaratne and Wolken (1998) found that the probability of a small firm having a line of credit did not decrease in the long run when there are fewer small banks in the area. Finally, after controlling for firm and owner characteristics and lender's financial condition, Cole and Walraven (1998) found that banks in markets where mergers have occurred are not more likely than other banks to deny small business loan applications.

Small Business Lending in Low- and Moderate-Income Areas

If it is true that large banks devote a smaller portion of their loan portfolio to small businesses, then lending to small businesses in low- and moderate-income (LMI) areas may be particularly constrained due to the uniqueness of LMI small business lending.

Lending to small businesses in LMI areas involves different considerations than lending to small businesses elsewhere for both banks and public institutions. Certain banks have demonstrated that they view small business lending to LMI areas differently through the establishment of special intermediaries and programs to help finance small businesses such as consortium lending corporations, community development corporations, small business investment companies, SBA 504 certified development companies, and micro-loan programs (Board of Governors, 1997). Likewise, the government has recognized fair lending concerns in connection with lending to LMI areas through the passage of laws, particularly the Community Reinvestment Act of 1977 (CRA).[2]

One difference in approving loans to LMI areas is the greater reliance on the character of the principals (who are more likely to be LMI borrowers, themselves) of the small businesses. LMI entrepreneurs generally do not have the usual amount of collateral that their higher income counterparts do. Existing small businesses in LMI areas, also, may be less capitalized than the average small business. So, the good credit history of an LMI small business principal, more frequently, will have to play a greater role for a loan to be approved. Besides the credit history of a small business entrepreneur, the business knowledge level of LMI borrowers can play a role in the decision to lend. Often LMI owners of a new firm do not have the opportunity to gain from the experiences of a network of family and friends who are small business owners, themselves. This is beginning to be overcome by increasing use of institutional entrepreneurial education (Reznick, 1999). Therefore, LMI small business lending is differentiable from other small business lending due to the special role that personal characteristics of small business principals play.

A second difference between LMI small business borrowing and borrowing by firms elsewhere is the proximity of a local depository institution branch. Studies on branch presence in areas categorized by income show some findings that LMI areas have less bank branches present. Caskey (1992) finds that banks are "significantly underrepresented" in low-income neighborhoods located in Atlanta and New York City. He, however, does not find this to be true in the other cities in his study: Denver, San Jose, and Washington D.C. Avery, Bostic, Calem, and Canner (1997) find a reduction in the number of branches in low-income areas with high concentrations of businesses over the period 1975 through 1995. They also find, however, that low-income neighborhoods' branches per capita were higher than other neighborhoods at the beginning of the period studied. Without this proximity to a branch by LMI small business borrowers, there may be less opportunity to develop a relationship with a lender. However, it would not be expected that lack of a local branch would severely limit access to small business banking services because evidence from the 1993 National Survey of Small Business Finances indicate that small businesses do business with banks with branches far away from their own communities (Cole and Wolken, 1995).

A third cause for belief in the uniqueness of small business lending in LMI areas is based on the theory that banks ration small business credit (Frame, Srinivasan, and Woosley, 1998). Because lenders have imperfect information to predict the probability of default by a small business borrower, they may lend less than the optimal amount of small business credit in the case that they had reliable means of predicting default probabilities. Banks may ration more small business credit in LMI areas due to the questionable economic health of the area where applicants do or will do business.

A fourth difference for small business lending in LMI areas is based on CRA related pressures that may offset the constraint of loans to small businesses in LMI areas. The public also views small business lending in LMI areas with special attention. Banks are often charged with discriminatory practices in lending through either outright discriminatory tastes of the lender or disparate impact of loan evaluation factors unrelated to the race, gender, age, and similar characteristics of loan applicants.[3] Fair lending laws, the CRA in particular, provide incentives to banks to actively try to meet the credit needs of LMI areas. Because merger applications are reviewed with consideration of whether or not the merging entities combined meet the credit needs of LMI areas, banks that desire to obtain approval to merge with other institutions have implemented special programs for LMI area lending. For example, Citibank has a business lending program for most start-up businesses in which loans are evaluated on a case-by-case basis and require discussion with representatives of the bank.[4]

Credit Scoring

If larger institutions are indeed less likely to lend to small businesses, it may be due to the greater costs incurred by originating and monitoring loans relative to the loans' sizes and lesser profitability of small business lending relative to other activities. Technological changes that reduce costs and increase profitability in small business lending should, therefore, increase small business lending. Credit scoring is one such technological advance.

What Credit Scoring Is

Credit scoring is a method of evaluating the credit risk of loan applicants using historical data and statistical techniques. It is the process of assigning a single quantitative measure, the score, to represent the borrower's probable future loan performance. Credit scoring has been used for some time in underwriting consumer loans, notably credit cards, auto loans, and home equity loans, and is becoming more popular as a tool in mortgage origination. Only recently, however, have lenders used credit scoring to evaluate commercial loan applications.

Credit Scoring and Small Business Lending in General

Prior to the advent of credit scoring, small business loans were underwritten in a manner very similar to that used for larger commercial loans. However, the personal credit history of the small business owner is a strong predictor of the business' loan repayment prospects, especially for loans under $100,000 (Mester, 1997). Lenders can, therefore, draw on the expertise of consumer lenders in developing and using credit scorecards for small businesses. The smallest businesses are the least likely to have detailed financial statements and a financial history separate from the owners' and are most likely to have their loan applications evaluated by a scorecard.[5]

Financial institutions benefit from the use of scorecards in several ways. Credit scoring is both faster and less expensive than traditional underwriting. Since loan officers using credit scores do not have to review credit reports and financial statements, the time spent underwriting each loan can drop dramatically. For example, Barnett Banks reported a decrease in processing time from more than three weeks without scoring to less than a day with scoring (Lawson, 1995). Reducing the processing time reduces the personnel cost per loan to the bank, making small business loans more attractive and profitable. Spending less time on routine loans may also allow loan officers to spend more time on marginal applicants that need individual attention (Somerville, 1997). Lenders can also use scores, or the changes in credit scores, to monitor loans. This reduces monitoring costs, and allows banks to make loans outside their branch footprint, thereby further reducing the cost of lending. An expanded geographic lending area can benefit banks by helping them to diversify their loan portfolio. Credit scoring may also simplify securitization of small business loans, thereby increasing the availability of loanable funds.

Credit scoring may also be less costly in terms of time spent by applicants gathering the information needed to complete the application, because customers only need to provide the information used in the scoring system (Mester, 1997). Complete financial statements may not be necessary, a benefit for some small businesses. In addition, applicants will not have to wait as long for a response if the lender uses scoring. Finally, if scoring encourages more lenders to offer credit in a particular market, customers will benefit from increased availability of credit and better terms than would be available with fewer market competitors.

Credit scoring also improves the objectivity of loan underwriting. If a scorecard is used exclusively, then the same criteria are applied to all applicants regardless of their membership in a protected class.[6] Furthermore, the scorecard makes it easy for banks to document the relationship between the criteria and creditworthiness of the applicant in the case of factors having a disparate impact on a protected class of applicants (Mester, 1997).

As with any model, there are limitations to credit scorecards. Most of the models currently in use were developed in a prosperous period of our nation's history, and it is not yet known how well their predictions of loan performance will fare in the event of a economic downturn. For the scorecard to produce an accurate score, the sample of the population used to create the model must be similar to the applicants that the model will score. This has implications for the use of credit scoring on low- and moderate-income applicants, as these applicants may be underrepresented in the sample.

Credit Scoring and Small Business Lending in LMI Areas

One argument in support of credit scoring's positive effect on small business lending in LMI areas is that credit scoring lowers the costs of making smaller loans (Mester, 1997). Since the loan amount is so small (under $100,000), the interest income derived from these loans are often too small to cover the costs of originating them. Under-capitalized or young firms in LMI areas are likely to demand smaller-sized loans. By reducing the fixed costs of originating loans, credit scoring allows banks to provide more small business loans in LMI areas.

A second argument is that credit scoring allows banks to be more willing to make loans in new or marginal markets because of greater confidence in assessing the probability of default (Mester, 1997). In other words, credit scoring banks would not have to credit ration in LMI areas, markets that tend to be considered generally riskier.

A third argument is that owners of start-up small businesses in LMI areas will have a greater chance of obtaining a loan from a bank that uses a credit scoring model because the model gives major weight to a business principal's credit rating (Mester, 1997). Therefore, new firm organizers in LMI areas whose firms do not have much of a cash flow history have better chances at receiving business loans if they have good personal credit histories. Also, the use of a principal's credit rating contributes to the lower costs of originating small business loans because of the ease of obtaining information from a credit bureau (Board of Governors, 1997).

A fourth argument points out that credit scoring does not necessarily replace individualized attention to loan applicants. In fact, credit scoring might improve a lender's attention to certain borrowers. The time saved from scoring allows a loan officer to focus on borrowers who need specialized attention (Somerville, 1997). Karl Zollinger of Whitney Holding Corporation, for example, claimed that credit scoring only plays a part in the whole loan decision-making process.[7]

A fifth argument is that credit scoring can equalize the playing field by standardizing the criteria for making a loan, thereby reducing subjectivity (Mester, 1997). Because a lender that uses an automated evaluation procedure does not have to see the borrower, a loan officer with a taste for discrimination would be less able to act on her prejudices. Skeptics of credit scoring's positive impact on fair lending cite some of the same factors in claiming that credit scoring *reduces* small business loans to LMI areas. One concern is that the population sample used to construct credit scoring models does not properly represent the LMI sub-population. Avery, Bostic, Calem, and Canner (1997) found that this may be a warranted concern by constructing a sample of credit history scores from data provided by a credit bureau. Another concern is that credit scoring models have been constructed from data collected during national prosperity. In the event of a recession, would credit scoring diminish lending to "at risk" applicants in LMI areas where a national recession may have a disparate effect (Somerville, 1997)? A third concern is based on the uniqueness of small business lending in LMI areas. Small business loan applications in these areas might require more individualized attention because of their uniqueness. Credit scoring, however, moves the borrower further away from interaction with the lender by taking the evaluation process to an impersonal computer model's score on a borrower (Somerville, 1997).

Research Question

This research adds to the current body of knowledge by examining lending by both scoring and non-scoring banks in LMI areas, using an extensive data set of demographic, business, banking, and survey data. Specifically, we explore whether banks employing credit scoring are less likely to lend in LMI areas, controlling for branch presence in the area.

Data

Demographic

Using software provided by the Census Bureau, LandView III, we compile tract demographic data collected from the last decennial census. Our sample includes the following characteristics for each census tract: persons, families, households, races, median household income, and housing units owned by occupant. LandView, however, does not provide median household income on the metropolitan area level. For these data, we used our branch deposits data source, SNL Securities.

Small Business

Data acquired by the Federal Reserve System from Dun and Bradstreet describe the total number of businesses located in every tract in the United States. For our study, we use the data broken down by the number of small businesses in a tract by annual revenue.

Banking

Small business lending in 1997 is measured by small business loan originations geo-coded by each institution in each census tract of all the metropolitan areas of Alabama, Florida, Georgia, Louisiana, Mississippi, and Tennessee. These small business lending data come from new information filed under the CRA with the Federal Financial Institutions Examination Council (FFIEC). The CRA small business loan amounts are measured by both number and dollars in three size categories: loans under $100,000; loans between $100,000 and $250,000; and loans between $250,000 and $1 million.

Institutions report branch deposits as of June 30, 1997 with the FDIC on the Summary of Deposits Report. These data, compiled by SNL Securities, Inc., are merged with institutions' small business lending by tract. Some branches' tracts are not identified by SNL Securities, and some branches' counties were misreported with the FDIC. Using a mapping program, MARPLOT, that utilizes the Census Bureau's TIGER/Line file and basic map features such as roads, corrections were made by the authors for branch data whose tracts or counties were incorrectly or insufficiently reported.

Survey

The survey data were collected by means of a telephone survey of the 200 largest banking companies, (as measured by total domestic assets of the bank or its holding company as of June 30, 1997). The Federal Reserve Bank of Atlanta conducted the survey in January 1998. The institutions in the survey sample jointly account for more than 70 percent of U.S. domestic banking assets and more than half of all small business loans as reported on the Report of Condition and Income as of June 30, 1997. The sample was further limited to exclude credit card banks and institutions with less than 0.5 percent of their total assets in small business loans as of June 30, 1997. These exclusions reduced the sample size to 190; and 99 institutions responded, for a response rate of 52.1 percent.

As of January 1, 1998, 62.6 percent of the respondents used credit scoring in originating small business loans, and an additional 11.1 percent planned to begin doing so before June 30, 1999. All of the scoring banks used a scorecard for loans less than $100,000 and 73.3 percent used a scorecard for loans less than $250,000. Only 21.7 percent of respondents scored larger loans. Responding banks used credit scoring to automatically approve or reject loans (41.7 percent), as part of the loan decision process (98.3 percent), in setting terms and conditions (32.3 percent), and in loan monitoring (12.9 percent). The vast majority of institutions that used the credit score to auto-decision small business loans did so for loans under $50,000. Only financial institutions that used scoring as all or part of the loan decision process are considered "credit-scorers" for the purposes of this study.

Most credit scorers (75.8 percent) used scoring to increase their small business lending market share within their current branch footprint, while only four of the scoring banks (6.5 percent) had used scoring to expand their geographic lending area. Finally, the majority (87.1 percent) of scorers used a purchased scorecard, with Fair, Isaacs being the most commonly used model.

Methodology

Combination of Data Sets

Our basic unit of data is the activity of a given lender in a particular census tract. The master data set is composed of five data sets (demographic, small business, CRA small business loan, deposits, and survey data) which we merged by institution per tract. To compare the small business lending between tracts of various median incomes, demographic information is taken for each tract. It is expected that various factors other than tract income may affect the amount of small business lending by an institution. Therefore, other demographics such as population, number of small businesses, and bank branch data are also noted for each tract.

The study looks at all urban census tracts in Alabama, Florida, Georgia, Louisiana, Mississippi, and Tennessee. By only including urban tracts in our study, we are able to both keep our sample size manageable and control for possible significant differences in lending patterns between rural and urban areas. Census tracts are useful to the study of lending patterns according to community income levels because they are defined by the Census Bureau according to geography and common socio-economic characteristics. The tracts in our sample are defined as either low-income, moderate-income, middle-income, or high-income. A tract's income level is identified by tract median household income expressed as a percent of the relevant metropolitan area median household income. Low-income tracts' median household income is less than 50 percent of the metropolitan median household income. Moderate-income tracts' median household income is between 50 and 80 percent. Middle-income tracts' median household income is between 80 and 120 percent. High-income tracts' median household income is over 120 percent of the MSA median household income.

The lenders examined in this study are limited to those banks that responded to our survey. Each of these banks reports small business loans under CRA. Our sample, therefore, excludes all institutions for which we do not have survey data. The remaining institutions originate about half of the small business loans in the urban areas of the six states considered. We only look at loans under $100,000 because nearly all our survey respondents that credit scored said they credit score loans under $100,000. A significant number did not credit score small business loans of larger amounts.

Potential Weakness of the Data

Our small business data are reported by tract. However, not all tracts are identified by Dun & Bradstreet, thereby excluding some tracts from consideration.

Another potential weakness of the data is the misidentification in the CRA filings of where a loan was made. Bostic and Canner (1998) point out that this could occur through the reporter's right to choose in reporting a loan between location of the business headquarters and where the loan money will be used. Another source of misidentification is that these loans can be reported where the business has a post office box. Neither of these considerations, however, should produce more than a small distortion to our information of where loans are made. With regard to reporting a loan where a business's headquarters are located, Bostic and Canner point out that the 1993 National Survey of Small Business Finances show that 84 percent of businesses have only one office, and 95 percent have no more than two offices. With regard to reporting a loan where a business has a post office box, it can be assumed that businesses will most likely have their post office boxes close to where they operate. If the post office box in question is outside of the business operation's census tract, the box would most likely be in an adjacent tract which probably has a similar level of median household income.

Our branch data have a small potential weakness in that approximately ten percent of branches reported by SNL Securities do not have tracts assigned to them by SNL Securities. We, therefore, assigned a tract to each, branch by branch, according to street address, longitude, and latitude which are provided by SNL Securities. Since some branches are close to tract borders, the assignment of a branch's tract can be imprecise. Therefore, there is some inconsistency in tract assignment for branches since some tracts were not assigned by the same source.

Empirical Analysis

Comparative Statistics

To answer the question of whether there are differences between credit scoring and non-credit scoring banks in lending to small businesses to LMI tracts, several tables are constructed. These tables break down the number of tracts where credit scoring banks ("scorers") and non-credit scoring banks ("non-scorers') made small business loans by income and average size of total lending by an institution in a tract. Given the survey results and the existing information regarding the size of small business loan most appropriate for scoring, we define "small business loan" as "loans to businesses with origination amounts of $100,000 or less." Tables 2.1 and 3.1 consider small business activity in a tract by introducing a control variable that represents market demand relative to other tracts.[8] In these tables, average bank lending per institution is expressed as a ratio to total revenue of small businesses in the tract.[9] Statistics are tabulated separately for out-of-market and for in-market lenders. An in-market lender, for the purposes of our study, is defined as having at least one branch in the tract where the loan is made. We distinguish loans made by banks that have nearby branches because branch proximity to applicants may allow for greater relationship between the borrower and lender. Tables 2.2 and 3.2 are the same as Tables 2.1 and 3.1 except they do not control for small business activity in a tract; these tables' bank lending in a tract is not divided by total small business revenue in the tract.

While Tables 2.1 through 3.2 express means of the average institution lending per tract by scoring and non-scoring banks, Graphs 4.1 through 5.2 give a graphical representation of the number of tracts with varying levels of lending by scoring and non-scoring banks. These graphs do not reflect any test for significance.

Regression Analysis

We run a regression to control for variables that may impact small business lending. We denote a dummy variable (CS) that takes a value of one for institutions that credit scored small business loans as of June 1997.

The dollar volume of small business loans in a given census tract is not only a function of an institution's decision to credit score. Several other factors may lead to variation in the level of small business lending. We expect that various tract characteristics impact the likelihood that a small business loan would be originated. Total small businesses (TOTBUS) in a tract may affect the size of total small business credit need. The sizes of those businesses may also affect the size of credit demanded (ABUS, BBUS, CBUS, DBUS, EBUS, FBUS, and GBUS). Another tract variable, the total housing units (UNITS), may affect total demand for small businesses' goods and services.[10] A tract, however, with many housing units may be one without many businesses, thus having a negative effect on total small business loan origination. The median household income level (INCOME) of a tract may affect total loan origination. (If the relative income of a community to its entire metropolitan area is not a *possible* influence, then there would be no motivation for this research.) Besides tract-wide characteristics, we expect the proximity of a bank branch to positively influence total origination of small business credit by the particular bank. Therefore, we include total branches of the lending institution in the tract (BRCH) in the regressions. Per the earlier discussion on institution size on availability of small business credit, the total assets (ASSETS) are expected to have a correlation to lending.

We use a regression model to estimate the predictors of total small business loans under $100,000 (SBL) by bank, *i*, in tract, *t*, as a ratio of assets (ASSETS) of bank, *i*. Our dependent variable is a ratio of small business loans in a tract to total institution size rather than straight small business loans because of concern that CS_i and $ASSETS_i$ are collinear. We run three regressions, one which includes all tracts, another that includes only low-income tracts, and another that includes only moderate-income tracts, using the following model:

$$\frac{SBL_{it}}{ASSETS_i} = a + yCS_i + \beta_1 TOTBUS_t + \beta_2 ABUS_t + \beta_3 BBUS_t + \beta_4 CBUS_t$$
$$+ \beta_5 DBUS_t + \beta_6 EBUS_t + \beta_7 FBUS_t + \beta_8 GBUS_t + \beta_9 UNITS_t + \beta_{10} INCOME_t$$
$$+ \beta_{11} BRCH_{it} + \beta_{12} AL + \beta_{13} FL + \beta_{14} GA + \beta_{15} LA + \beta_{16} MS + u_{it}$$

where

CS = credit scoring dummy variable

TOTBUS = total businesses,

ABUS = number of businesses reporting less than $49,000 in revenue / TOTBUS,

BBUS = number of businesses reporting between $50,000 and $99,000 in revenue / TOTBUS,

CBUS = number of businesses reporting between $100,000 and $249,000 in revenue / TOTBUS,

DBUS = number of businesses reporting between $250,000 and $499,000 in revenue / TOTBUS,

EBUS = number of businesses reporting between $500,000 and $999,000 in revenue / TOTBUS,

FBUS = number of businesses reporting between \$1,000,000 and \$4,999,000 in revenue / TOTBUS,
GBUS = number of businesses reporting between \$5,000,000 and \$9,999,000 in revenue / TOTBUS,
UNITS = number of housing units,
INCOME = tract median household income / metro median household income * 100,
BRCH = number of institution branches,
AL = Alabama,
FL = Florida,
GA = Georgia,
LA = Louisiana, and
MS = Mississippi.

To see if credit scoring has a different impact in low- and moderate-income areas, we compare the coefficient for CS_i of each regression. If credit scoring has a relatively positive (negative) effect on the ratio of loans in a tract to lender size in low- and moderate-income areas, we would expect a greater (lesser) coefficient on CS_i for regressions including only low- and moderate-income tracts.

We run regressions using a similar model, but with a focus on a different coefficient. Because we are interested in the total amount of credit made available by scoring and non-scoring banks and want to control for institutional factors that may be correlated with whether or not a bank credit scores small business loans, we run similar regressions for all scorer loans (SBL_{it}) in all tracts and for all non-scorer loans in all tracts. We replace the $INCOME_t$ variable with three dummy variables representing the income category of the tract where the loan is made, LOW_t (low-income tract), MOD_t (moderate-income tract), and MID_t (middle-income tract). We compare the coefficients on the LOW_t and MOD_t variables between the scorer and non-scorer loan regressions. We expect that if the income level of a community has less predictive power of the amounts of loans made by scoring banks, then the absolute values of the coefficients for LOW_t and MOD_t would be less for the scorer regression than non-scorer regression.

The nature of loan data, however, presents problems for estimation of the above nature. Most banks in our sample do not report small business lending in every tract in the Southeast. No consideration of the absence of lending by some institutions diminishes the relative measurement of the lending activity of banks that do make loans in tracts. If we include institutions' "zero loans," though, we encounter another problem: an ordinary least squared regression would be biased because the loan value is a limited dependent variable, *i.e.* the value of total loans per tract by an institution is limited to being no less than zero. This limited nature of the dependent variable is problematic because "zero loans" cannot indicate the various proclivities of banks to make loans given different predictive factors when no loans are made. Estimators obtained through an ordinary least squares regression would tend towards insignificance, therefore, because the influences of the various independent variables cannot be observed when a bank does not make any loans in a tract. To deal with the above problems inherent in the type of data that we are studying, we take two regression approaches. The first is an ordinary least squares regression of all tracts where banks made small business loans in the Southeast. The second is a tobit regression (Tobin, 1958) of all tracts in the Southeast, which includes the “zero loans” made by every surveyed institution in every tract. The tobit model is a frequently used method to deal with limited dependent variables. Creation of the “zero loan” observations expands our data set beyond the computing capacity available to us. Therefore, all the tobit regressions are broken into six regressions, one for each state in our sample.

Results—Comparative Statistics

Difference in Average Lending Between Scorers and Non-Scorers

The most simple method of answering the question of whether there are disparate small business lending patterns between credit scoring banks and non-credit scoring banks is comparison of average total tract lending between scorers and non-scorers in each income tract category. Table 2.1 summarizes these statistics with control for small business activity estimated by total small business revenue generated in each tract. Table 2.2 presents the same type information without controlling for small business revenue. We assume that the amount of small business activity may be a significant indicator of the demand for small business credit, so we focus on Table 2.1. We will then compare Table 2.2 with 2.1 to explore differences in results when there is no control for small business revenue.

On average, *out-of-market* scorers originate *more* small business loans relative to small business revenue than non-scorers (seven basis points more) in low-income tracts, but less in the other, higher income tracts (moderate-income: eight basis points less, middle-income: two basis points less, and high-income: two basis points less). None of these differences, however, is statistically different than zero. See the Out-of-Market section of Table 2.1.

On average, *in-market* scorers originate *less* small business loans relative to small business revenue than non-scorers in every income category of tracts (low-income: three basis points less; moderate-income: six basis points less; middle income: 52 basis points less; and high-income: 38 basis points less). In all tracts but low-income, these differences are statistically different from zero. See the In-Market section of Table 2.1.

Overall, Table 2.1 shows that there is not a significant disparity between average total small business lending per tract to small business revenue per tract between *out-of-market* scorers and non-scorers. Though not significant, out-of-market scorers' average ratio of total tract small business lending to total small business revenue is greater than non-scorers' in low-income tracts, while the reverse is true in higher income tracts. There is a significant disparity between average total small business lending in a tract to small business revenue between *in-market* scorers and non-scorers, however, in moderate-, middle-, and high-income tracts. The disparity is very small in moderate-income tracts in comparison to the higher income tracts. With regard to in-market lending, therefore, we see that non-scorers have a greater investment in small business loans relative to business revenue than scorers in the two highest income categories. However, this difference is not as great in LMI tracts.

Table 2.2 yields mostly similar results as Table 2.1 in terms of the statistics' significance and signs. The difference in loans to small business revenue between out-of-market scorers and non-scorers, however, has the opposite sign in low-income tracts. Also, the differences between out-of-market scorers and non-scorer loans are statistically significant in middle-income and high-income tracts.

Differences in the Distribution of Average Lending between Scorers and Non-Scorers

Another way of looking at our research question is by comparing the distribution of average total tract lending by scorers and non-scorers across tracts of different income categories. These statistics are controlled for small business activity and summarized in Table 3.1. Graphs 4.1, 4.2, 5.1, and 5.2 supplement the statistics presented in Table 3.1. Table 3.2 presents the same statistics without control for small business activity (There are no graphs that correspond to Table 3.2). For the same reasons presented in the discussion on Tables 2.1 and 2.2, we focus on Table 3.1 and discuss Table 3.2 only to explore differences in results when there is no control for small business revenue.

On average, *out-of-market* scorers originate more loans to total small business revenue in low-income tracts than high-income tracts (14 basis points more). This difference between low- and high-income lending of scorers is over three times the difference for non-scorers (five basis points more). Neither of these differences, however, are statistically different than zero. See the Out-of-Market section of Table 3.1. Graphs 4.1 and 4.2 show similar findings: there is a greater percentage of low-income tracts where scorers lend which have the highest amounts of loans per small business revenue (greater than 1.0 percent) than of higher income categories (Graph 4.1). On the other hand, the distribution of tracts of various sized average tract lending activity to small business revenue by out-of-market non-scorers is more even across the tracts (Graph 4.2).

On average, *in-market* scorers originate about the same amount of small business loans to small business revenue in low- and high-income tracts (one half a basis point difference and not statistically significant). In-market non-scorers, however, originate significantly less total small business loans per institution to small business revenue in low-income tracts than high-income tracts (34 basis points less). See the In-Market section of Table 3.1. Graphs 5.1 and 5.2, however, shed more light on these statistics. Graph 5.1 shows similar results as the In-Market Scorer section of Table 3.1. Graph 5.2, however, shows an extraordinarily high percentage of low-income tracts with very high in-market non-scorer loans to small business revenue: 36.84 percent of low-income tracts where in-market non-scorers are active have average non-scorer total lending per institution that are greater than 2.0 percent of total small business revenue. This statistic for non-scorer low-income tracts is about twice as large as that of the other non-scorer tracts. Therefore, while in-market non-scorers lend significantly less in low-income tracts than high-income tracts, Graph 5.2 shows that the numerical difference does not tell the whole story and that in-market non-scorers are lending a peculiarly large amount in many low-income tracts.

When looking at the differences between lending in *moderate*-income and high-income tracts, we see that both out-of-market scorers and non-scorers lend less to moderate-income tracts than high-income tracts. Scorers' difference is over two times as great as non-scorers (Ten basis points for scorers versus four basis points for non-scorers.) Neither difference, though, is statistically different from zero. In-market, both scorers and non-scorers lend more in moderate-income tracts than high-income tracts. In-market non-scorer lending difference between moderate- and high-income tracts, however, is about fifty times greater than that of scorer lending (22 basis points for non-scorers versus one half a basis point for scorers). Neither of these differences are statistically different from zero.

Overall, Table 3.1, Graphs 4.1, 4.2, 5.1, and 5.2 show us that scorers originate more loans in low-income tracts where they are active than high-income tracts where they are active, for both out-of-market and in-market lending. This is true in the absolute sense and in comparison to non-scorer trends. However, with respect to moderate-income tract lending, scorers lend less than in high-income tracts absolutely when lending out-of-market and relatively less in both out-of-market and in-market lending. But, some of these mean lending differences are not statistically significant.

Table 3.2 yields some different results when small business revenues are used as a control variable. Out-of-market scorers lend less, though not significantly so, in low-income tracts than in high-income tracts. In-market scorers, however, lend significantly more dollars in low-income tracts than high-income tracts ($58,986 more). Out-of-market and in-market non-scorers lend less in low-income tracts than high-income tracts. The differences, however, are not statistically significant. In moderate-income tracts, all lenders originate less, and significantly so, for in-market scorers. The difference in results from Table 3.1, especially in signs, indicates the importance of small business revenue in considering small business lending.

Results—Regressions

We estimate our two regression models against two data sets. Our first set of regression estimates indicate the factors that affect the ratio of small business loans originated by surveyed banks in a tract divided by the total assets of the bank that originated the loans (SBL_{it}/ $ASSETS_i$).[11] In the regressions, using the data set that includes only observations for positive loans, all estimates of the credit scoring (CS_i) coefficient are significant. The estimates show that a credit scoring institution was more likely to have a higher small business loan to asset ratio in a low-income or moderate-income tracts than in higher income tracts (Table 6). In the regressions using the data set that includes "zero loans" made by the surveyed banks in each tract, we find similar results for Alabama, Georgia, and Tennessee (Tables 8.1, 8.3 and 8.5). The Florida regression estimates that CS_i for low- and moderate-incomes is less than for all tracts. The coefficient for moderate-income, however, is not significant (Table 8.2). Credit scoring estimates for Louisiana and Tennessee, however, do not have statistical significance (Tables 8.4 and 8.6). The lack of significance may be due to correlation problems between institutional variables in the models.[12]

Our second set of regressions present strong results indicating that more small business loans are likely to be originated in LMI tracts by scoring banks than non-scoring banks.[13] The dependent variable in these regressions is total small business loans originated by a particular institution in a tract (SBL_{it}). We run three types of regressions using this model: one that includes all observations, another that includes only scorer loans, and another that includes only non-scorer loans. We run these regressions using two different data sets: one that excludes "zero loans" and the other that includes "zero loans." The regressions using the data set that only includes observations for positive loans show that the dummy variable equaling one if the tract receiving a loan is low-income (LOW_t) is more negative for non-scoring institutions (–51.2) than scoring ones (–12.4). Both these estimates are statistically significant. Likewise, among scoring institutions, whether or not a tract is moderate-income is less important than among non-scoring institutions. For scorers, the estimate on the moderate-income dummy variable (MOD_t) is –9.9 while for non-scorers, it is –33.6. Both estimates are statistically significant (Table 7).

Regressions using the data set that is inclusive of "zero loan" observations show similar results for the LOW_t estimate in Alabama, Georgia, Mississippi, and Tennessee (Tables 9.1, 9.3, 9.5, and 9.6). Opposite results, however, occurred for Florida and Louisiana (Tables 9.2 and 9.4). Regressions using the more inclusive data set show the same type of results as the regressions using the exclusive data set for the MOD_t estimate.

All regressions indicate certain variables other than credit scoring and the median household income of a tract seems to very significantly influence the amount of small business loan originations. One is the number of branches of the lender that are present in a tract. Note in Tables 7 and 9.1 through 9.6 that, overall, the $BRCH_{it}$ variable is positively significant for all tracts. Among scorers, however, branch presence has less of an effect on total originations in a tract than among non-scorers. Note that this does not hold true in the Alabama and Mississippi regressions. Another significant variable in these regressions is the total businesses in the tract variable ($TOTBUS_t$). The estimate on the coefficient for this variable is positive and statistically significant in nearly every regression that we ran. See Tables 6 through 9.6 for further detail.

Conclusions

The growing application of credit scoring to the small business lending process has invited claims by some banking observers, on one hand, that the automated process expands banks' ability to offer small business credit in low- and moderate-income communities. Banking observers, on the other hand, have claimed the opposite, asserting that credit scoring reduces credit to small businesses in low- and moderate-income communities. Research into how credit scoring has impacted small business credit in low- and moderate-income communities, therefore, is important to the policymaker whose objective is to foster fair lending by credit scoring banks.

This paper, using a data set that is a compilation of geo-coded loan data, branch and deposit data, small business data, demographic data, and credit scoring survey data, presents the results of comparing univariate statistics, ordinary least squares, and tobit regression models, which control for various institution- and tract-specific variables. We conclude four major points. First, banks that credit scored small business loans generally originated more loans in low-income areas relative to other areas. Second, banks that credit scored small business loans generally originated moderately more loans in moderate-income areas relative to other areas. Third, branch presence is a significant factor in the amount of small business loans that are originated in any tract. The importance, however, decreases for scorers. Fourth, consideration of small business activity in a tract is important. We also suggest ideas for improvement on the research techniques described in this paper.

Overall, these results show that institutions that credit score small business loans are likely to lend more in low-income areas than non-scorers are. The absolute differences in the ratio of out-of-market scorer and non-scorer loans to total small business revenue in low-income tracts are not statistically different from zero, while the difference of in-market non-scorer minus scorer loans is significantly more in higher-income tracts. Also, among in-market lenders, scorers lend significantly more in low-income tracts than high-income tracts as opposed to non-scorers. The regressions show that credit scoring has a mostly positive effect on the ratio of loans to total assets in low-income tracts as opposed to all other tracts. The regressions also show, overall, that a tract being low-income affects the amount of small business loans made by scorers less negatively than non-scorers. Scorers are likely to lend $12,400 less in moderate-income tracts than other tracts where they are active, while non-scorers are likely to lend $51,200 less (Table 7). Four individual state regressions that include “zero loan” observations show similar results.

Overall, scorers are likely to lend more in moderate-income tracts than non-scorers. The comparative statistics do not show that scorers statistically lend more on average than non-scorers in moderate-income tracts do. The regressions, however, show that a scoring bank tends to lend more as a ratio of its total assets in moderate-income tracts than non-scorers do. Like the results for low-income tracts, the regressions that include “zero loans” have varying support for this assertion depending on the state. The regressions also show that a scorer is likely to lend $9,900 less in moderate-income tracts than other tracts where they are active, while non-scorers are likely to lend $33,000 less (Table 7). All the individual state regressions that include “zero loan” observations show similar results for moderate-income tracts.

Branch presence is an important influence on the amount of lending in a tract. However, we find that branch presence has different implications for the amount of loans made by scorers and non-scorers. Overall, our regressions show that branch presence positively and significantly affects lending. We also see that, except for Alabama and Florida, all of the models which estimate total small business lending in a tract (SBL_{it}) show that the number of branches of a lender has less impact for scorers than non-scorers. This may indicate that scorers are more likely to lend further away from where they have a physical presence.

Our results show the importance of considering small business activity in tracts where loans are made. The comparative statistics give different results when not controlling for the amount of business activity in a tract, and nearly all our regressions show that the total number of businesses in a tract is a significant factor that affects lending in any tract. Not considering this factor may provide skewed results, particularly if the amount of small business activity in a tract tends to be correlated with the median household income of that tract.

The findings presented here are only the beginning of further research into disparate lending patterns of scorers and non-scorers in LMI areas. Our regression models can be improved through further efforts to control for interactions between various institutional variables, such as whether or not an institution credit scores, total assets, and small business loan ratios. The regressions including "zero loans" should be improved by running a single regression for the whole Southeast rather than for each individual state. This combination would improve the significance levels of our estimates by increasing the sample size of non-censored values in regressions for states with fewer loan observations. The regressions can also be improved through the addition of 1996 CRA small business lending data, so that comparisons between lending by institutions that did not credit score in 1996 but did in 1997 can be made.

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TABLE 1

Survey Results for Credit-Scoring Banks

Data as of January 31, 1998

	Number	Percent of Scoring Banks
Loan Sizes Scored:		
Under $100,000	62	100.0
$100,000 - $250,000	46	74.2
$250,000 - $1,000,000	13	21.0
How Scoring Used:		
Automatic Approval/Rejection	26	41.9
Part of Decision Process	59	98.3
Setting Loan Terms	20	32.3
Monitoring Existing Loans	8	12.9
Type Scorecard Used:		
Proprietary	8	12.9
Purchased	54	87.1
Avg. Months Scoring	24	---

TABLE 2.1

Average Small Business Total Loans (< $100,000) Divided by Small Business Revenue: Differences between Scorers and Non-Scorers by Tract

	Mean	Standard Deviation	Sample Size
Out-of-Market			
Low Income Tracts			
Scorers	0.0072442	0.0160774	542
Non-Scorers	0.0065076	0.0140218	267
Difference	0.0007366		
Difference t-statistic	*0.668732*		
Moderate Income Tracts			
Scorers	0.0048787	0.0106264	1213
Non-Scorers	0.0056954	0.0122409	451
Difference	-0.0008167		
Difference t-statistic	*-1.25227*		
Middle Income Tracts			
Scorers	0.0070595	0.0545052	2375
Non-Scorers	0.0072883	0.0210134	1054
Difference	-0.000188		
Difference t-statistic	*-0.17706*		
High Income Tracts			
Scorers	0.0058687	0.0170658	1511
Non-Scorers	0.0060567	0.0165097	897
Difference	-0.000188		
Difference t-statistic	*-0.26678*		
In-Market			
Low Income Tracts			
Scorers	0.0021355	0.0058688	419
Non-Scorers	0.0024227	0.008032	75
Difference	-0.0002872		
Difference t-statistic	*-0.29585*		
Moderate Income Tracts			
Scorers	0.0021293	0.00552	1304
Non-Scorers	0.0080427	0.025552	184
Difference	-0.0059134**		
Difference t-statistic	*-3.12893*		
Middle Income Tracts			
Scorers	0.0025835	0.0359534	3568
Non-Scorers	0.0077518	0.0263754	494
Difference	-0.0051683***		
Difference t-statistic	*-3.88417*		
High Income Tracts			
Scorers	0.0020806	0.004322	2545
Non-Scorers	0.0058427	0.0121334	438
Difference	-0.0037621*		
Difference t-statistic	*-6.41939*		

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 2.2

**Average Small Business Total Loans (< $100,000):
Differences between Scorers and Non-Scorers by Tract**

	Mean	Standard Deviation	Sample Size
Out-of-Market			
Low Income Tracts			
Scorers	104.29557746	112.4041918	781
Non-Scorers	110.9745547	196.0615006	393
Difference	-91.765726		
Difference t-statistic	*-0.62555*		
Moderate Income Tracts			
Scorers	103.5283951	318.3602559	1215
Non-Scorers	110.1086475	156.4975905	451
Difference	-52.9691954		
Difference t-statistic	*-0.56071*		
Middle Income Tracts			
Scorers	92.8068995	89.8734214	2377
Non-Scorers	113.3206831	157.2654164	1054
Difference	-64.4585169***		
Difference t-statistic	*-3.95791*		
High Income Tracts			
Scorers	106.9543349	130.5259175	1511
Non-Scorers	121.1906355	178.7948042	897
Difference	-71.8404693*		
Difference t-statistic	*-2.07849*		
In-Market			
Low Income Tracts			
Scorers	206.5634844	257.5608125	618
Non-Scorers	232.0855856	270.5012631	148
Difference	-63.9377787		
Difference t-statistic	*-1.04043*		
Moderate Income Tracts			
Scorers	126.1178517	120.7220779	1304
Non-Scorers	261.7918919	401.1761341	185
Difference	-283.7056094***		
Difference t-statistic	*-4.57063*		
Middle Income Tracts			
Scorers	118.2391199	148.9664308	3568
Non-Scorers	259.195108	401.9447293	494
Difference	-283.7056094***		
Difference t-statistic	*-7.72129*		
High Income Tracts			
Scorers	147.5772751	202.3791106	2545
Non-Scorers	271.073516	420.9234091	438
Difference	-273.346134***		
Difference t-statistic	*-6.02166*		

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 3.1

Average Small Business Total Loans (< $100,000) Divided by Small Business Revenue: Differences between Tracts by Scorers and Non-Scorers

	Mean	Standard Deviation	Sample Size
Out-of-Market			
Scorers			
Low Income Tracts	0.0072442	0.0160774	542
High Income Tracts	0.0058687	0.0170658	1511
Difference	0.0013755		
Difference t-statistic	*1.6808760*		
Moderate Income Tracts	0.0048787	0.0106264	1213
High Income Tracts	0.0058687	0.0170658	1511
Difference	-0.0009900		
Difference t-statistic	*-1.8517152*		
Non-Scorers			
Low Income Tracts	0.0065076	0.0140218	267
High Income Tracts	0.0060567	0.0165097	897
Difference	0.0004509		
Difference t-statistic	*0.4420930*		
Moderate Income Tracts	0.0056954	0.0122409	451
High Income Tracts	0.0060567	0.0165097	897
Difference	-0.0003613		
Difference t-statistic	*-0.4530048*		
In-Market			
Scorers			
Low Income Tracts	0.0021355	0.0058688	419
High Income Tracts	0.0020806	0.0043220	2545
Difference	0.0000549		
Difference t-statistic	0.1834672		
Moderate Income Tracts	0.0021293	0.0055200	1304
High Income Tracts	0.0020806	0.0043220	2545
Difference	0.0000487		
Difference t-statistic	*0.2779156*		
Non-Scorers			
Low Income Tracts	0.0024227	0.0080320	75
High Income Tracts	0.0058427	0.0121334	438
Difference	-0.0034200**		
Difference t-statistic	*-3.1268546*		
Moderate Income Tracts	0.0080427	0.0255520	184
High Income Tracts	0.0058427	0.0121334	438
Difference	0.0022000		
Difference t-statistic	*1.1162319*		

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 3.2

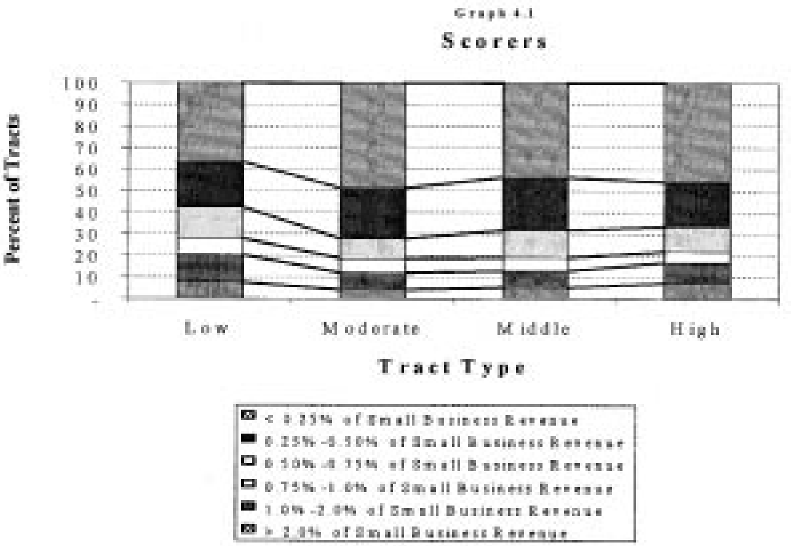
Average Small Business Total Loans (< $100,000): Differences between Tracts by Scorers and Non-Scorers

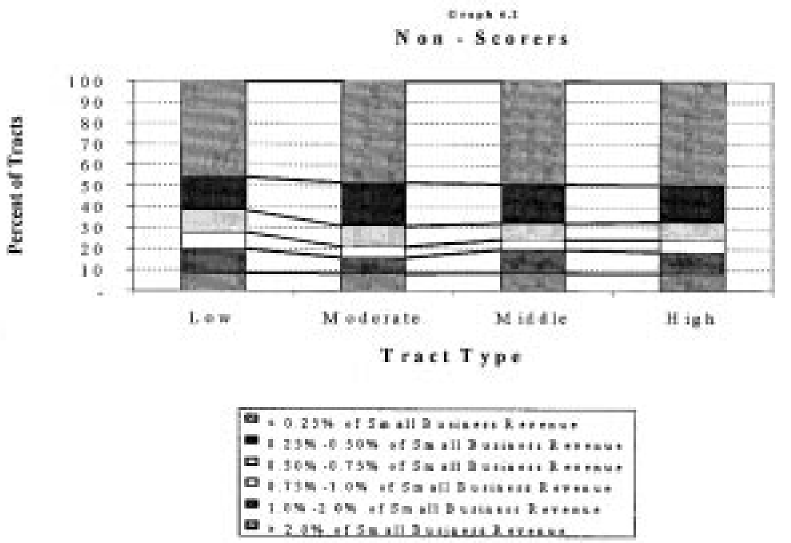
	Mean	Standard Deviation	Sample Size
Out-of-Market			
Scorers			
Low Income Tracts	104.2957746	112.4041918	781
High Income Tracts	106.9543349	130.5259175	1511
Difference	-2.6585603		
Difference t-statistic	*-0.5074021*		
Moderate Income Tracts	103.5283951	318.3602559	1215
High Income Tracts	106.9543349	130.5259175	1511
Difference	-3.4259398		
Difference t-statistic	*-0.3520621*		
Non-Scorers			
Low Income Tracts	110.9745547	196.0615006	393
High Income Tracts	121.1906355	178.7948042	897
Difference	-10.2160808		
Difference t-statistic	*-0.8843507*		
Moderate Income Tracts	110.1086475	156.4975905	451
High Income Tracts	121.1906355	178.7948042	897
Difference	-11.0819880		
Difference t-statistic	*-1.1685129*		
In-Market			
Scorers			
Low Income Tracts	206.5634844	257.5608125	618
High Income Tracts	147.5772751	202.3791106	2545
Difference	58.9862093***		
Difference t-statistic	*5.3092146*		
Moderate Income Tracts	126.1178517	120.7220779	1304
High Income Tracts	147.5772751	202.3791106	2545
Difference	-21.4594234***		
Difference t-statistic	*-4.1094110*		
Non-Scorers			
Low Income Tracts	232.0855856	270.5012631	148
High Income Tracts	271.0735160	420.9234091	438
Difference	-38.9879304		
Difference t-statistic	*-1.3003848*		
Moderate Income Tracts	261.7918919	401.1761341	185
High Income Tracts	271.0735160	420.9234091	438
Difference	-9.2816241		
Difference t-statistic	*-0.2599914*		

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

GRAPHS 4.1—4.2

Average Out-of-Market Loans as Percent of Small Business Revenue in a Tract





GRAPHS 5.1—5.2

Average In-Market Loans as Percent of Small Business Revenue in a Tract

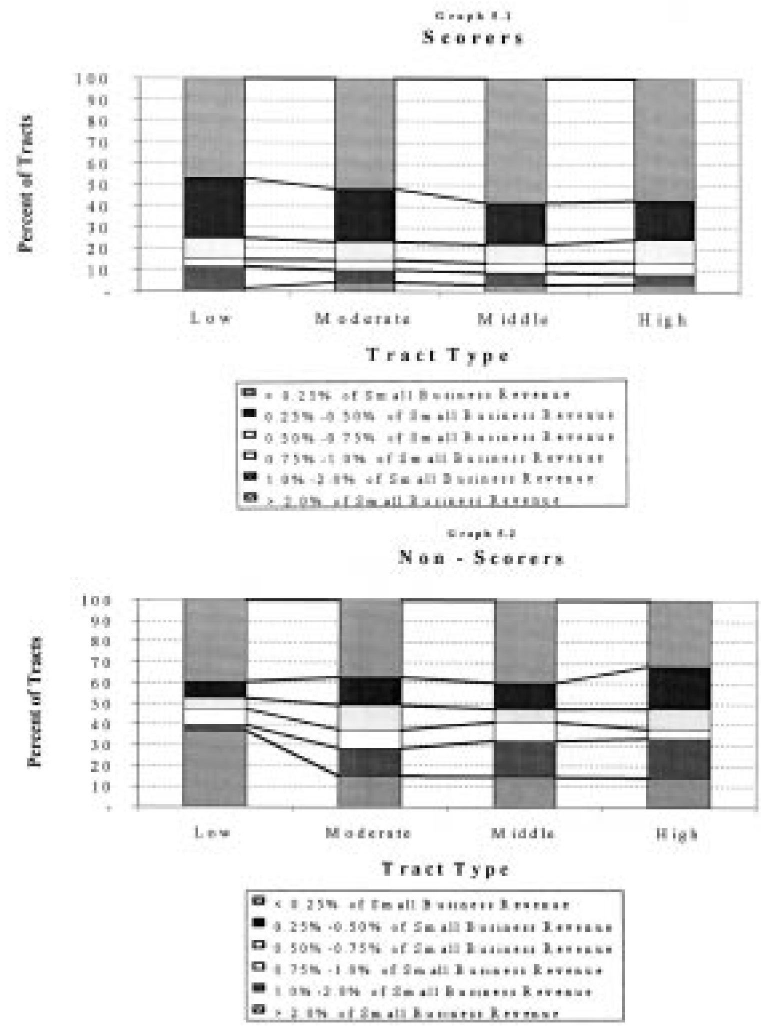


TABLE 6

Ordinary Least Squared Regressions

Excludes Institutions that Make No Loans in a Tract

Dependent Variable: SBL_{it} / $ASSETS_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression t-Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Regression t-Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Regression t-Statistics
Intercept	1.852 E –5	0.888	5.278 E –5	0.889	6.724 E –5	1.311
CS	-1.515 E –5	-17.626***	-1.219 E –5	-3.331***	-1.102 E –5	-5.438***
ABUS	-6.431 E –8	-0.299	-0.291 E –6	-0.451	-0.941 E –6	-1.794
BBUS	4.427 E –9	0.021	-0.491 E –6	-0.784	-0.643 E –6	-1.231
CBUS	-0.106 E –6	-0.498	-0.386 E –6	-0.627	-0.560 E –6	-1.080
DBUS	2.1108 E –8	0.096	-0.102 E –6	-0.150	-0.422 E –6	-0.804
EBUS	-9.364 E –9	-0.039	-0.273 E –6	-0.367	-0.650 E –6	-1.106
FBUS	4.530 E –8	0.181	-0.337 E –6	-0.467	-0.367 E –6	-0.605
GBUS	-3.013 E –8	-0.071	-0.890 E –6	-0.723	-1.428 E –6	-1.449
TOTBUS	2.848 E –8	18.606***	2.486 E –8	4.805***	1.270 E –8	2.797**
UNITS	-8.263 E –10	-3.824***	2.489 E –11	0.019	1.410 E –9	2.337**
INCOME	1.881 E –8	2.322*	-0.140 E –6	-0.871	0.102 E –6	1.098
BRCH	1.887 E –6	2.960**	-1.948 E –6	-0.608	-0.833 E –6	-0.535
ASSETS	-3.772 E –14	-8.631***	-3.624 E –14	-1.796	-3.691 E –14	-3.722***
AL	0.312 E –6	0.229	1.273 E –6	0.221	0.194 E –6	0.063
FL	-1.229 E –6	-1.167	-2.061 E –6	-0.454	-4.708 E –6	-1.959
GA	-4.298 E –6	-3.971***	-2.814 E –6	-0.546	-4.644 E –6	-1.608
LA	7.073 E –6	5.465***	3.287 E –6	0.631	7.018 E –6	2.411**
MS	2.494 E –5	12.724***	3.210 E –5	4.071***	1.722 E –5	3.713***
# of Observations	17,655		1,320		3,253	
R2	0.0751		0.0554		0.0467	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 7

Ordinary Least Squared Regressions

Excludes Institutions that Make No Loans in a Tract

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	78.440	0.571	7.167	0.045	218.670	0.811
ABUS	-0.417	-0.294	0.551	0.334	-2.874	-1.037
BBUS	-0.116	-0.083	0.353	0.216	-0.911	-0.326
CBUS	-0.677	-0.483	0.324	0.199	-2.754	-0.999
DBUS	0.556	0.383	1.412	0.845	-1.243	-0.423
EBUS	0.411	0.259	1.057	0.575	-0.726	-0.228
FBUS	2.330	1.419	3.078	1.609	0.988	0.307
GBUS	-0.853	-0.305	0.899	0.282	-4.511	-0.776
TOTBUS	0.213	21.140***	0.232	20.506***	0.163	7.543***
UNITS	-0.004	-2.571**	-0.003	-2.161*	-0.002	-0.673
BRCH	13.034	3.116**	-7.466	-1.654	83.488	7.819***
ASSETS	-0.301 E-6	-11.184***	-0.322 E-6	-11.479***	-1.287 E-6	-3.414***
AL	65.948	7.380***	55.160	5.243***	104.932	5.754***
FL	-10.410	-1.461	-14.382	-1.930	5.371	0.305
GA	17.412	2.144*	4.607	0.494	78.483	4.248***
LA	43.456	5.111***	36.860	3.894***	75.528	3.992***
MS	80.981	6.305***	-0.436	-0.027	185.726	7.780***
LOW	-23.850	-2.649**	-12.386	-1.223	-51.164	-2.664***
MOD	-12.649	-1.962*	-9.923	-1.402	-33.595	-1.880
MID	-17.791	-3.454***	-17.911	-3.146**	-21.850	-3.414***
# of Observations	17,674		13,634		4,039	
R2	0.0563		0.602		0.0740	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 8.1

Tobit Model: Alabama

Dependent Variable: SBL$_{it}$/ ASSETS$_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression Chi-Squared Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Chi-Squared Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Chi-Squared Statistics
Intercept	-1.396 E –6	3.279	-4.035 E –6	0.985	4.694 E –6	1.664
CS	-6.670 E –7	110.322***	-3.457 E –7	3.305	-6.049 E –7	16.546***
ABUS	-1.317 E –8	0.953	-3.785 E –9	0.008	-8.421 E –8	5.569**
BBUS	-2.246 E –8	2.791	-1.071 E –8	0.066	-1.014 E –7	7.483**
CBUS	-2.174 E –8	2.364	-8.778 E –9	0.045	-7.187 E –8	3.824
DBUS	-2.100 E –8	2.335	-1.440 E –8	0.122	-8.176 E –8	4.957*
EBUS	-2.660 E –8	2.900	-1.224 E –8	0.066	-1.067 E –7	5.905**
FBUS	-2.746 E –9	0.029	1.347 E –9	0.001	-3.883 E –8	0.844
GBUS	-2.883 E –8	1.213	-2.464 E –8	0.112	-1.938 E –7	6.005**
TOTBUS	4.372 E –9	194.559***	5.339 E –9	68.297***	4.162 E –9	35.472***
UNITS	-6.824 E –11	3.369	1.654 E –10	1.413	-1.419 E –10	1.593
ASSETS	-5.543 E –16	1.050	-7.731 E –16	0.217	-6.596 E –16	0.275
LEVEL	2.210 E –9	10.472**	-1.732 E –9	0.019	-1.189 E –8	2.109
BRCH	1.096 E -5	17525.65***	1.107 E –5	5151.017***	1.072 E –5	412.177
Noncensored Values	1,510		119		282	
Left Censored Values	54,065		5,891		11,140	

TABLE 8.2

Tobit Model: Florida

Dependent Variable: SBL$_{it}$/ ASSETS$_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression Chi-Squared Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Chi-Squared Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Chi-Squared Statistics
Intercept	-1.030 E –4	24.923***	-7.110 E –6	5.063*	-4.516 E –6	7.040**
CS	-2.033 E –7	9.626**	-3.739 E –7	5.428*	-6.688 E –8	1.791
ABUS	1.064 E –8	0.248	1.361 E –8	0.160	8.884 E –9	0.260
BBUS	5.247 E –9	0.063	1.347 E –8	0.178	8.931 E –9	0.266
CBUS	-2.857 E –9	0.019	5.166 E –9	0.026	1.733 E –8	1.035
DBUS	1.707 E –11	6.231 E –7	2.059 E –8	0.334	1.600 E –8	0.829
EBUS	7.416 E –9	0.108	1.151 E –8	0.118	1.394 E –8	0.504
FBUS	5.964 E –9	0.060	3.002 E –8	0.719	2.717 E –8	2.043
GBUS	2.192 E –8	0.487	-4.059 E –8	0.264	7.990 E –8	6.213**
TOTBUS	4.844 E –9	1513.721***	3.549 E –9	155.671***	8.812 E –10	32.961***
UNITS	-1.481 E –10	68.632***	-8.450 E –11	2.434	4.702 E –11	8.991**
ASSETS	-2.505 E –16	25.256***	-2.454 E –16	0.036	8.374 E –16	4.827**
LEVEL	2.856 E –9	4.873*	-8.258 E –9	1.442	-4.312 E –9	2.128
BRCH	8.439 E –6	2326.902***	9.816 E –6	298.023***	3.215 E –6	399.068***
Noncensored Values	6,010		308		1,127	
Left Censored Values	209,562		15,073		42,782	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 8.3

Tobit Model: Georgia

Dependent Variable: SBL_{it} / $ASSETS_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression Chi-Squared Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Chi-Squared Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Chi-Squared Statistics
Intercept	-6.489 E –6	20.078***	-9.075 E –7	1.376	-2.765 E –6	0.773
CS	-5.898 E –7	88.740***	-1.254 E –7	10.090**	-4.225 E –7	20.192***
ABUS	1.117 E –8	0.552	-7.151 E –9	0.741	-8.647 E –9	0.078
BBUS	1.121 E –8	0.585	-4.968 E –9	0.408	-4.443 E –9	0.020
CBUS	5.598 E –9	0.143	-2.304 E –9	0.082	-1.946 E –8	0.375
DBUS	9.833 E –9	0.409	-4.379 E –9	0.296	-8.312 E –9	0.065
EBUS	1.341 E –8	0.699	-4.000 E –9	0.204	-1.04 E –9	0.001
FBUS	2.019 E –8	1.336	-1.712 E –9	0.033	3.843 E –10	1 E –4
GBUS	1.903 E –8	0.363	-3.925 E –9	0.083	-4.919 E –8	0.679
TOTBUS	9.690 E –11	0.192	4.349 E –10	4.543**	4.168 E –10	0.981
UNITS	6.535 E –11	4.935**	-6.393 E –11	3.383	-9.394 E –10	9.782**
ASSETS	1.053 E –15	4.557*	2.223 E –16	0.507	9.367 E –16	1.592
LEVEL	1.912 E –9	8.522**	2.650 E –9	2.087	-9.394 E –10	0.027
BRCH	8.994 E –6	6426.841***	4.114 E –6	9470.897***	6.309 E –6	587.367***
Noncensored Values	2,039		176		334	
Left Censored Values	81,338		12,443		17,211	

TABLE 8.4

Tobit Model: Louisiana

Dependent Variable: SBL_{it} / $ASSETS_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression Chi-Squared Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Chi-Squared Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Chi-Squared Statistics
Intercept	-0.101 E –4	5.041*	-2.666 E –6	1.001	-0.028 E –4	2.597
CS	-7.569 E –8	0.287	-4.093 E –9	0.001	4.214 E –7	0.976
ABUS	-3.971 E –8	0.754	-2.107 E –8	0.616	8.860 E –9	0.003
BBUS	-3.382 E –8	0.550	-1.390 E –8	0.260	6.707 E –8	0.148
CBUS	-3.155 E –8	0.475	-1.359 E –8	0.250	8.187 E –8	0.213
DBUS	-2.647 E –8	0.325	-1.758 E –8	0.411	1.156 E –7	0.410
EBUS	-3.684 E –8	0.557	-2.221 E –8	0.543	1.083 E –7	0.336
FBUS	-2.702 E –8	0.287	-2.054 E –8	0.425	8.838 E –8	0.229
GBUS	-1.984 E –9	0.001	-5.516 E –8	0.870	-6.889 E –8	0.070
TOTBUS	8.697 E –9	237.680***	7.085 E –9	151.261***	7.511 E –9	33.286***
UNITS	3.267 E –10	14.283***	-2.189 E –10	4.449*	1.277 E –9	16.958***
ASSETS	-2.748 E –15	5.6230*	-1.561 E –15	2.196	-3.304 E –15	0.904
LEVEL	3.272 E –9	4.766*	-1.811 E –9	0.086	1.024 E –8	0.170
BRCH	1.834 E –4	53.412***	1.642 E –5	5415.949***	-5.048 E –6	0.032
Noncensored Values	1,838		184		373	
Left Censored Values	78,054		12,220		17,829	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 8.5

Tobit Model: Mississippi

Dependent Variable: $SBL_{it}/ASSETS_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression Chi-Squared Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Chi-Squared Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Chi-Squared Statistics
Intercept	2.785 E –5	3.081**	1.076 E –4	2.118	1.624 E –5	0.971
CS	-3.157 E –6	43.460***	-3.405 E –6	2.863	-1.998 E –6	16.266***
ABUS	-5.217 E –7	10.310**	-1.389 E –6	3.691	-2.985 E –7	2.746
BBUS	-5.200 E –7	10.147**	-1.481 E –6	3.837	-2.512 E –7	2.068
CBUS	-4.813 E –7	8.954**	-1.429 E –6	4.017*	2.404 E –7	1.993
DBUS	-5.055 E –7	9.615**	-1.330 E –6	2.839	-2.938 E –7	2.552
EBUS	-4.373 E –7	5.891**	-1.179 E –6	1.844	-2.425 E –7	1.362
FBUS	-5.141 E –7	9.076**	-1.469 E –6	2.274	-2.913 E –7	2.532
GBUS	-4.768 E –7	4.120*	-1.320 E –6	2.268	-3.987 E –7	1.679
TOTBUS	-4.293 E –10	0.033	-1.527 E –9	0.038	4.052 E –9	1.438
UNITS	7.579 E –10	6.013**	8.204 E –10	0.135	6.300 E –10	2.009
ASSETS	1.464 E –17	1.3 E –5	1.004 E –15	0.003	-1.724 E –15	0.145
LEVEL	1.323 E –8	5.245*	-1.322 E –7	0.402	-1.663 E –8	0.264
BRCH	6.496 E –5	12953.970***	2.092 E –5	8.765**	4.397 E –5	7236.028***
Noncensored Values	5,005		42		93	
Left Censored Values	20,760		3,014		4,929	

TABLE 8.6

Tobit Model: Tennessee

Dependent Variable: $SBL_{it}/ASSETS_i$

Regressor	All Tracts Regression Coefficients	All Tracts Regression Chi-Squared Statistics	Low Income Tracts Regression Coefficients	Low Income Tracts Chi-Squared Statistics	Moderate Income Tracts Regression Coefficients	Moderate Income Tracts Chi-Squared Statistics
Intercept	-4.573 E –6	10.253***	-4.541 E –6	9.879**	-9.546 E –6	2.371
CS	-2.376 E –8	0.098	-5.173 E –9	0.001	6.242 E –8	0.081
ABUS	-2.348 E –8	2.519	6.847 E –9	0.184	-2.223 E –7	11.669***
BBUS	-1.205 E –8	0.655	-8.753 E –10	0.003	-1.647 E –7	6.582**
CBUS	-2.010 E –8	1.881	1.746 E –9	0.0120	-1.908 E –7	8.933**
DBUS	-1.993 E –8	1.434	4.838 E –9	0.076	-2.085 E –7	9.855**
EBUS	-2.153 E –8	1.670	4.408 E –10	4.74 E –4	-2.147 E –7	11.097***
FBUS	1.736 E –8	0.929	2.746 E –8	2.041	-1.471 E –7	3.628
GBUS	1.503 R –9	0.002	1.366 E –8	0.104	-1.988 E –7	4.714**
TOTBUS	2.087 E –9	52.160***	2.866 E –9	62.231***	1.906 E –9	2.642
UNITS	-1.423 E –11	0.116	1.085 E –10	0.752	-6.925 E –11	0.189
ASSETS	-2.283 E –15	13.441***	-3.155 E –15	6.602**	-1.950 E –15	1.212
LEVEL	3.136 E –9	14.956***	-7.376 E –9	1.618	2.149 E –9	2.588
BRCH	1.068 E -5	2529.882***	1.535 E -5	5537.471***	1.347 E -5	449.922***
Noncensored Values	1,855		204		343	
Left Censored Values	64,995		8,869		13,270	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 9.1

Tobit Model: Alabama

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	-1121.448	13.285***	-899.945	6.474**	-1536.894	7.297**
ABUS	0.857	0.075	-0.967	0.0726	4.159	0.525
BBUS	-2.651	0.726	-3.604	1.013	-0.913	0.025
CBUS	-1.152	0.125	-2.554	0.463	1.431	0.057
DBUS	1.349	0.180	-0.627	0.029	4.885	0.690
EBUS	1.238	0.122	-0.272	0.004	3.911	0.361
FBUS	3.316	0.815	1.437	0.114	6.642	0.975
GBUS	-3.195	0.279	-5.927	0.698	1.229	0.013
TOTBUS	0.383	35.550***	0.361	23.177***	0.420	13.072***
UNITS	0.007	0.722	0.009	0.954	0.002	0.016
ASSETS	3.299 E –7	10.773***	3.108 E –7	9.876**	5.513 E –6	43.508***
BRCH	868.692	717.253***	808.100	447.061***	630.608	263.407***
LOW	-117.953	20.340***	-92.204	9.178**	-161.855	11.572***
MOD	-59.534	9.127**	-55.440	5.626**	-64.803	3.472
MID	-49.645	9.927**	-376.26	4.099*	-69.348	6.113**
Noncensored Values	1,510		915		595	
Left Censored Values	54,065		33,564		20,501	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 9.2

Tobit Model: Florida

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	-739.334	27.031***	-628.068	16.218***	-1103.296	9.521**
ABUS	-2.156	2.105	-2.323	2.034	-2.253	0.364
BBUS	-1.298	0.803	-1.794	1.274	0.872	0.058
CBUS	-0.140	0.010	-0.780	0.248	2.910	0.662
DBUS	0.359	0.058	-0.332	0.041	3.504	0.884
EBUS	0.222	0.201	-0.569	0.109	3.743	0.964
FBUS	2.924	3.003	-2.497	1.818	5.136	1.476
GBUS	-0.094	0.002	-0.720	0.084	3.037	0.342
TOTBUS	0.112	261.035***	0.117	210.120***	0.097	48.270***
UNITS	0.004	15.085***	0.004	9.810**	0.007	9.165**
ASSETS	1.142	1950.285***	9.173 E –7	1242.197***	1.536 E –7	17.659***
BRCH	396.361	2257.068***	359.724	1843.931***	746.079	361.206***
LOW	-51.691	29.183***	-61.575	32.649***	-14.686	0.508
MOD	-25.850	17.578***	-17.355	6.598**	-76.149	23.018***
MID	-15.946	10.318***	-10.782	3.862*	-45.473	14.501***
Noncensored Values	6,010		5,271		739	
Left Censored Values	209,562		128,207		81,355	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 9.3

Tobit Model: Georgia

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	-1426.566	32.173***	-1113.188	21.631***	-2005.004	12.713***
ABUS	2.950	1.265	1.374	0.301	6.695	1.315
BBUS	1.829	0.520	1.345	0.310	2.924	0.266
CBUS	3.219	1.580	2.660	1.191	4.563	0.637
DBUS	4.067	2.337	4.014	2.544	2.780	0.214
EBUS	4.199	2.294	3.262	1.537	6.623	1.138
FBUS	8.074	7.245**	6.502	5.148*	10.982	2.733
GBUS	10.312	3.642	8.740	2.965	10.509	0.725
TOTBUS	0.093	8.328**	0.0936	9.370**	0.117	2.725
UNITS	0.019	16.415***	0.010	4.676*	0.036	12.193**
ASSETS	1.576 E–6	677.857***	1.285 E–6	582.547***	1.394 E–5	385.644***
BRCH	552.806	939.133***	359.568	507.011***	861.980	393.247***
LOW	-119.039	39.941***	-85.648	22.930***	-178.769	18.011***
MOD	-87.698	35.541***	-57.057	16.776***	-159.126	23.039***
MID	-50.381	18.264***	-38.543	11.608***	-72.976	8.102**
Noncensored Values	2,039		1,320		719	
Left Censored Values	81,338		50,338		31,000	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 9.4

Tobit Model: Louisiana

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	-1293.200	5.950**	-1256.858	3.361	-1114.035	2.763
ABUS	-5.474	1.032	-6.576	0.891	-2.538	0.139
BBUS	-6.193	1.340	-7.564	1.194	-2.629	0.151
CBUS	-3.051	0.325	-4.905	0.503	0.640	0.009
DBUS	-3.785	0.487	-4.891	0.486	-1.093	0.026
EBUS	-0.113	3.83 E–4	-1.819	0.059	2.724	0.142
FBUS	-3.163	0.281	-3.985	0.266	-0.912	0.015
GBUS	3.306	0.125	6.524	0.291	-2.152	0.033
TOTBUS	0.5666	102.421***	0.636	75.023***	0.380	31.509***
UNITS	0.065	47.181***	0.069	30.427***	0.048	17.579***
ASSETS	1.024 E–6	98.128***	8.667 E–7	52.888***	1.558 E–6	4.994**
BRCH	992.372	31.247***	966.976	20.005***	977.495	13.847***
LOW	-131.782	23.231***	-132.830	14.048***	-107.667	9.856**
MOD	-78.214	12.789***	-72.709	6.528**	-74.468	7.519**
MID	-55.515	8.958**	-58.811	5.822**	-39.442	3.111
Noncensored Values	1,838		1,333		505	
Left Censored Values	78,054		48,253		29,801	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 9.5

Tobit Model: Mississippi

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	1642.921	4.094*	669.232	1.747	3320.965	2.763
ABUS	-29.196	12.232**	-14.025	7.197**	-45.831	5.036*
BBUS	-31.314	14.002***	-13.709	6.908**	-55.278	7.198**
CBUS	-27.784	11.425**	-12.368	5.801**	-47.552	5.557**
DBUS	-32.224	14.798***	-15.124	8.369**	-51.910	6.360**
EBUS	-22.418	5.822**	-8.620	2.205	-43.421	3.639
FBUS	-31.647	12.469***	-13.993	6.242**	-55.204	6.333**
GBUS	-16.804	1.917	-4.206	0.322	-41.946	1.878
TOTBUS	0.119	1.085	0.127	3.470	-0.113	0.134
UNITS	-0.022	1.875	0.013	1.662	0.020	0.231
ASSETS	3.017 E –7	2.798	2.062 E –7	5.066*	-0.288 E –4	18.276***
BRCH	594.601	417.648***	4462.014	141.320***	1277.193	197.697***
LOW	-197.742	17.046***	-110.352	13.123***	-281.903	5.869**
MOD	-126.308	11.575***	-73.246	9.541**	-148.511	2.819
MID	-29.970	1.038	-3.972	0.048	-96.913	1.718
Noncensored Values	505		304		201	
Left Censored Values	20,760		12,885		7,875	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

TABLE 9.6

Tobit Model: Tennessee

Dependent Variable: SBL_{it}

Regressor	Scorers and Non-Scorers Regression Coefficients	Scorer and Non-Scorer Regression t-Statistics	Scorer Regression Coefficients	Scorer Regression t-Statistics	Non-Scorer Regression Coefficients	Non-Scorer Regression t-Statistics
Intercept	-840.855	25.125***	-935.644	19.638***	-621.160	4.922*
ABUS	-1.361	0.610	0.625	0.083	-6.687	4.813*
BBUS	0.054	0.001	1.424	0.429	-2.331	0.609
CBUS	0.933	0.298	2.436	1.291	-2.152	0.560
DBUS	1.288	0.462	2.637	1.291	-1.232	0.131
EBUS	0.146	0.006	1.628	0.491	-2.856	0.683
FBUS	4.629	4.898*	5.139	3.862*	5.024	2.019
GBUS	2.643	0.546	5.422	1.640	-4.587	0.436
TOTBUS	0.189	52.449***	0.234	61.933***	0.062	1.233
UNITS	0.020	22.787***	0.015	10.411***	0.036	16.589***
ASSETS	5.937 E –7	142.497***	4.028 E –7	62.310***	-1.440 E –6	4.221
BRCH	471.875	851.332***	448.074	664.057***	511.056	167.014***
LOW	-35.948	6.947**	-32.527	4.316*	-44.946	2.658
MOD	-34.345	9.329**	-20.421	2.578	-81.489	11.235***
MID	-24.929	7.365**	-13.120	1.574	-64.979	11.279***
Noncensored Values	1,855		1,479		376	
Left Censored Values	64,995		39,950		25,045	

* greater than 95 percent significance
** greater than 98 percent significance
*** greater than 99.9 percent significance

Notes

1 The survey revealed that 36 percent of small businesses used credit cards as their primary source of funding, up from 17 percent in 1993.

2 The distinction between an LMI area and LMI borrower should be made here. An LMI area is an entire neighborhood whose median household income is under a certain percentage of the median household income of the neighborhood's entire metropolitan area. A LMI borrower, however, is one whose personal income is below a certain percentage of metropolitan median household income. An LMI borrower, therefore, is not necessarily any borrower who uses loan money to finance a business in an LMI area. However, we do expect a higher incidence of borrowing in LMI areas to be by LMI borrowers.

3 J. Seiberg. "Activists: Banks Short-Change Small Businesses in the Inner City" *American Banker* 162 (25 November 1997): p. 4.

4 S. Abdur-Rahman and G. D. Gallop. "Citigroup Banks on Small Business." *Black Enterprise* 29 (October 1998): pp. 30-31.

5 The Board of Governors of the Federal Reserve System reported to Congress in 1997 that, "[there is an] emerging consensus that one of the most powerful predictors of the performance of small business loans is the credit history of the owner, independent of any financial information of the firm."

6 Lenders must continue to exercise care in overriding the model and handling marginal borrowers to avoid violating fair lending laws.

7 S. Stuart. "Scoring Speeds the Borrowing Process, but Are the Results Fair?" *New Orleans City Business* 18 (12 January 1998): pp. 18-19.

8 Small business activity is represented by a total of the small business revenues generated in each tract. The total revenues had to be approximated, however, by taking the number of businesses in each revenue range (up to one million dollars) defined by Dun and Bradstreet, multiplying them by the midpoint dollar amounts of those ranges, and summing the products for each tract. Since this method is used consistently across all tracts, the approximation is valid for comparison between tracts.

9 Observing only the amount of small business revenue, however, does not control for possible differences in demand for bank credit by firms between LMI tracts and higher income tracts.

10 Preliminary regressions were run using various variables related to total housing units such as total residents. Housing units had the only statistically significant coefficient.

11 We originally regressed our independent variables on the straight loans originated in the tract without division by assets. We found, however, that whether or not an institution credit scored is positively correlated with the asset size of the institution. To control for the problem in estimating coefficients of a regression that contains correlated variables, we changed the dependent variable to a ratio of loans in the tract to assets of the bank. This still does not perfectly control for institutional-level correlations, however, because the ratio of small business loans in a tract to a lender's total assets is also correlated with the institutions' total small business loan to total assets ratio. We found that, for the institutions in our sample, this ratio is negatively correlated with total assets. Therefore, more work is needed on these regressions. Our results presented

here, however, are still useful because we draw conclusions from the comparison of coefficients on the credit scoring dummy variable between regressions for all tracts, low-income tracts only, and moderate-income tracts only. Additionally, preliminary results from regressions that include the institutions' overall small business loan-to-assets ratio do not significantly differ from the ones presented in this paper.

[12] See note 11.

[13] We ran similar regressions using the number of loans in a tract and obtained similar results.

References

Abdur-Rahman, Sufiya and Gerda D. Gallop. "Citigroup Banks on Small Business," *Black Enterprise*, 29, October 1998, pp. 30-31.

Avery, Robert B., Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner. "Consolidation and Bank Branching Patterns," presented at the Federal Reserve Bank of New York's Conference on the Consolidation of the Financial Services Industry, March 1998.

_______. "The Distribution of Credit Scores: Findings and Implications for the Provision of Financial Services," *Proceedings: 33rd Annual Conference* on Bank Structure and Competition, May 1997, pp. 521-536.

Berger, Allen and Gregory Udell. "Relationship Lending and Lines of Credit in Small Firm Finance," *Journal of Business*, 68, July 1995, pp. 351-381.

_______. "Universal Banking and the Future of Small Business Lending," in *Financial System Design*: *The Case for Universal Banking*, edited by A. Saunders and I. Walter, Irwin Publishing, Homewood, Illinois, 1996.

Board of Governors of the Federal Reserve System. *Report to Congress on the Availability of Credit to Small Businesses*, Washington, D.C., October 1997.

Bostic, Raphael W. and Glenn B. Canner. "New Information on Lending to Small Businesses and Small Farms: The 1996 CRA Data," *Federal Reserve Bulletin*, 84, January 1998, pp.1-21.

Caskey, John P. "Bank Representation in Low-Income and Minority Urban Communities," Working Paper Number 92-10, Federal Reserve Bank of Kansas City, December 1992.

Cole, Rebel A. and John D. Wolken. "Financial Services Used by Small Businesses: Evidence from the 1993 National Survey of Small Business Finances," *Federal Reserve Bulletin*, 81, July 1995, pp. 629-640.

Cole, Rebel A. and Nicholas Walraven. "Banking Consolidation and the Availability of Credit to Small Businesses," presented at the Federal Reserve Bank of New York's Conference on the Consolidation of the Financial Services Industry, March 1998.

Elliehausen, Gregory and John Wolken. "Banking Markets and the Use of Financial Services by Small and Medium-Sized Businesses," *Federal Reserve Bulletin*, 76, October 1990, pp. 801-817.

Frame, W. Scott, Aruna Srinivasan, and Lynn Woosley. "The Effect of Credit Scoring on Small Business Lending," presented at the annual conference of the Southern Finance Association, Marco Island, Florida, November 1998.

Jayaratne, Jith and John Wolken. "How Important are Small Banks to Small Business Lending? New Evidence from a Survey of Small Firms," presented at the Federal Reserve Bank of New York's Conference on the Consolidation of the Financial Services Industry, March 1998.

Keeton, William. "Multi-Office Bank Lending to Small Businesses: Some New Evidence," *Economic Review*, Federal Reserve Bank of Kansas City, 80, Second Quarter 1995, pp. 45-57.

Lawson, James C. "Knowing the Score," *U.S. Banker*, September 1995, pp. 61-65.

Mester, Loretta. "What's the Point of Credit Scoring?," *Business Review*, Federal Reserve Bank of Philadelphia, September / October 1997, pp. 3-16.

Nakamura, Leonard. "Monitoring Loan Quality via Checking Account Analysis," *Journal of Retail Banking*, 14, Winter 1992-1993, pp. 16-33.

Peek, Joe and Eric Rosengren. "Small Business Credit Availability: How Important is Size of Lender?," Working Paper Number 95-5, Federal Reserve Bank of Boston, April 1995.

_______. "The Evolution of Bank Lending to Small Business," *New England Economic Review*, Federal Reserve Bank of Boston, March / April 1998, pp. 27-36.

_______. "Bank Consolidation and Small Business Lending: It's not Just Bank Size that Matters," *Journal of Banking and Finance*, 22, August 1998, pp. 799-819.

Petersen, Mitchell and Raghuram Rajan. "The Benefits of Lending Relationships: Evidence from Small Business Data," *Journal of Finance*, 49, March 1994, pp. 3-37.

Reznick, Scott M. Interview with authors, Philadelphia, Pennsylvania, March 5,1999.

Seiberg, Jaret. "Activists: Banks Short-Change Small Businesses in the Inner City," *American Banker*, 162, November 25, 1997, p. 4.

Somerville, Mary T. "Credit Scoring and the Small-Business Lender," *Commercial Lending Review*, 12, Summer 1997, pp. 62-66.

Strahan, Philip and James Weston. "Small Business Lending and Bank Consolidation: Is There Cause for Concern?," *Current Issues in Economics and Finance*, Federal Reserve Bank of New York, 2, March 1996.

Stuart, Stephen. "Scoring Speeds the Borrowing Process, but Are the Results Fair?," *New Orleans City Business*, 18, January 12, 1998, pp. 18-19.

Tobin, James. "Estimation of Relationships for Limited Dependent Variables," *Econometrica*, 26, 1958, pp. 24-36.

Whalen, Gary. "Out-of-State Holding Company Affiliation and Small Business Lending," Office of the Comptroller of the Currency Economic and Policy Analysis, Working Paper Number 95-4, September 1995.

Zardkoohi, Asghar and James Kolari. "The Effect of Structural Changes in the U.S. Banking Industry on Small Business Lending," Department of Finance, Texas A&M University, manuscript.

THE DEVELOPMENT AND EXPANSION OF SECONDARY MARKETS FOR SMALL BUSINESS LOANS

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In 1994, Congress passed The Riegle Act to remove regulatory obstacles to the securitization of small business loans. The Act extended to securitized small business loans the same benefits extended to residential mortgage-backed securities.

Securitization is the process of packaging individual loans and other debt instruments, converting the package into a security, and enhancing the credit status or rating to further their sale to third-party investors (Kendall and Fishman, 1998). This process provides lenders with alternative sources of funding and fee income, and allows the lenders to reduce their exposure to credit and interest rate risks.

The market for securitized small business loans—separate and apart from those loans guaranteed by the U. S. Small Business Administration—appears to be developing more slowly than other asset-backed securities. One reason cited for the slow growth is the limited amount of information available on credit performance of small business loans. Assessing credit risk is a major obstacle to the development of small business related securities. In addition, the cost of collecting, analyzing, and disseminating information on the credit risk of a pool of small business loans is higher than the cost for a comparably-sized pool of far fewer, but much larger, commercial mortgages.

How do we increase the rate of securitization of small business loans? One recent new development—the introduction of credit scoring models for small business lending—is significantly reducing the cost of assembling and assessing the credit quality of small business loans. These credit scoring models estimate the relationship between information obtained from credit bureau reports or from loan applications and the likelihood of poor loan performance.

While credit scoring has overcome some of the most serious limitations of small-business lending—the lack of standardized lending terms and uniform underwriting guidelines—the rate of securitization of small business loans has not increased, as had been suggested, by the Board of Governors of the Federal Reserve System.

The principal reason that credit scoring has not increased the rate of securitization of small business loans is the favorable macroeconomic conditions that the economy is currently enjoying. A different macroeconomic condition, where everyone is not flush with liquidity, might create a greater demand for securitization, as banks seek relief from interest rate risk.[1]

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Introduction (Section I)

The secondary markets now play a major role in channeling funds to residential housing. These markets have been used to raise funds more dependably and at lower cost.

Inspired by this success, The Riegle Community Development and Regulatory Improvement Act of 1994 ("The Riegle Act") P. L. 103, included one title that removed regulatory obstacles to the securitization of small business loans. The Act extended to securitized small business loans the same benefits extended to residential mortgage-backed securities. These benefits include the elimination of state-level investment restrictions and securities-registration requirements, as well as the establishment of favorable federal regulatory treatment intended to reduce certain issuance and regulatory costs. In particular, investment restrictions for federally-regulated banks, thrifts, credit unions, and pension funds were relaxed.

Lenders securitize loans by pooling assets with similar characteristics, and selling interests in these loan pools to investors. This process provides lenders with alternative sources of funding and fee income, and allows the banks to reduce their exposure to credit and interest rate risks.

The market for securitizing small business loans—separate and apart from those loans guaranteed by the U. S. Small Business Administration (SBA)—appears to be developing slowly. Less than $2 billion of non-SBA guaranteed loans were reported to have been securitized as "rated offerings" through the first half of 1996 (see Exhibit A and C).[2] By comparison, there were $315 billion of outstanding commercial and industrial loans by commercial banks to small businesses at the end of June 1995. More than $370 billion in small business loans are outstanding today. Only a fraction has been marketed since 1996—a period during which other asset-backed securities have been growing rapidly.

One reason cited for the slow growth of securitized small business loans is the limited information available on credit performance. Assessing credit risk is a major obstacle to the development of small business related securities. In addition, the cost of collecting, analyzing, and disseminating information on the credit risk of a pool of small business loans is higher than the cost for a comparably-sized pool of far fewer, but much larger, commercial mortgages.

However, one recent development—the introduction of credit scoring models for small business lending—is likely to accelerate the systematic accumulation of more detailed information on credit risk. These credit scoring models estimate the relationship between information obtained from credit bureau reports and from loan applications and the likelihood of poor loan performance. The use of credit scoring models is expected to encourage the use of standardized lending terms, documentation, and underwriting guidelines which, in turn, should result in more refined estimates of loss-probability distributions.

This study focuses on the potential of using credit scoring models to reduce the cost of assembling small business loans. By automating the assessment of credit risk, one of the main obstacles to the development of secondary markets for small business loans is addressed. The next two sections develop the theoretical framework for securitization (Section II), and then examine the methodology used in this research (Section III). Section IV looks at the market for securitizing small-business loans, followed by Section V's discussion of credit scoring models. Section VI is the analysis. The study's conclusions are in Section VII.

Theoretical Framework (Section II)

Value-Added Process

What is securitization? Securitization is one of the most important and abiding innovations to emerge in financial markets since the 1930s. Securitization is the process of packaging individual loans and other debt instruments, converting the package into a security, and enhancing the credit status or rating to further their sale to third-party investors (Kendall and Fishman, 1998).

Thus, securitization is a process of "value-added." Securitization converts illiquid individual loans or debt instruments, which cannot be sold readily to third-party investors, into liquid, marketable securities. It accomplishes this by backing each pool of loans with specific collateral rather than through a general obligation of the issuing corporation. The asset-backed security is structured under applicable laws to stand on its own and to pass through to investors the timely payment of principal and interest.

Value Added Through Securitization.

Loans	Securities
Illiquid	Liquid / tradeable
Subjective collateral valuation	Market-determined value
Originator assesses risk and enhancers assess risk	Third-parties, credit rating agencies
Originator has high operating costs	Originator has low operating costs
Limited terms / rates	Mixture of terms and rates

Key Participants

The structure of the securitization process involves seven key participants, starting with the borrower and the loan originator. The originator may be responsible for servicing the loan, which includes collecting payments, keeping records, and collecting bad debts, however servicing rights are often sold as well.

A trust—a special-purpose entity formed solely to purchase the assets—is the third participant.[3] The entity controls the collateral, administers the collection of cash flow, and passes through principal and interest to the investors.

This, in turn, leads to our fourth and fifth participants—the credit rating agency and the credit enhancer. Most securitized assets are sold with triple-A ratings. Residential mortgage securities packaged by Fannie Mae and Freddie Mac are not rated, because of the implicit backing of the government. If sufficient protection against future losses is not provided by the securities, then additional guarantees must be provided through credit enhancements.

The amount of credit enhancement required by credit rating agencies to receive a triple-A rating varies. Residential mortgages and automobile loans are in the range of 8-15 percent. The less confident the credit rating firms are in their statistical estimates of future losses for any particular pool of loans, the greater the level of total credit enhancement required by these firms before conferring a triple-A rating. For small business loans that lack a repayment history, credit enhancements may be more expensive.

The sixth key participant is the investment banker, who is responsible for pricing the asset and marketing it to the investor, the seventh key participant in the securitization process is the investor.

- Borrower
- Loan Originator
- Special Purpose Trust ⇔ Credit Rating Agency ⇔ Credit Enhancer
- Investment Banker
- Investor

Basic Requirements

There are six basic requirements to establishing a successful securitization program.

First, a standardized risk contract provides all participants in the process with the confidence that the collateral exists in a form that will enable the parties to meet their contractual obligations. Next, the required evaluation or grading of risk by professional underwriters provides the parties with the necessary due diligence as to the nature of the risk.

Third, a database of historical statistics is needed to enable all interested parties to evaluate how the loan portfolio will perform under adverse conditions. Fourth, because securitization is a legal process, uniform laws and regulations are needed that spell out the rights of each party. These rights must be handled in a uniform manner across state lines. Fifth, the quality of loan servicing is also important.

Sixth, most credit backed securities sold in public debt markets to investors require a credit rating by one of the four national rating agencies. Depending on the type of loan loss anticipated, rating agencies require some type of credit enhancement. Credit enhancement firms absorb catastrophic loan loss.

- Standardized risk contracts
- Grading of risk via underwriting
- Database of historical statistics
- Uniform laws and regulations
- Standardization of servicer quality
- Reliable supply of quality credit enhancers

Benefits

The principal benefit of securitization has been the lowering of the cost of transferring funds from investors to borrowers. The cost of borrowing declines and the supply of funds increases, thus allowing lenders to make new loans and permitting borrowers to indirectly tap new funding sources.

- Benefits to borrowers → Lower cost of funds
- Benefits to originators → Liquidity
- Benefits to underwriters → Origination fees
- Benefits to investors → High-yielding securities

Loan originators also benefit from securitization through increased liquidity, enhanced profits, reduced risk, and increased specialization. At the same time, underwriters benefit from having a new product line and a continuous flow of fees. The securitization process is particularly important for non-depository lenders who cannot use deposits as a source of capital.

Finally, investors benefit by gaining access to new low-risk products that match risk/return needs, and provide a means toward diversifying investments.

Methodology (Section III)

Field Research

This study used the field-research methodology developed by Schutzman & Strauss (1973) and Kerlinger (1986). By its very nature, field research, while guided by initial conceptions of problems and issues, is a deductive process.

This study is based on interviews with scores of people involved in the securitization and credit scoring of small business loans.

Interviews were conducted in person and via phone. Other information was gathered through other research papers, government reports, the Federal Reserve Board, Fair, Isaac Inc., commercial banks, and other financial and lending institutions.

Category of Interviewee

- Lenders
- Government Agencies
- Small Business Groups
- Issuers of Securities
- Consultants
- Credit Rating Agencies
- Credit Scoring Companies
- Academics
- Securities Lawyers

The Market for Securitizing Small Business Loans (Section IV)

The potential size of the market for securitizing small business loans appears large when gauged by the amount of outstanding small business loans. As of June 30, 1998, commercial banks held roughly $370 billion in small business loans in original amounts of less than $1 million per loan. This volume of small business loans has expanded by about, on average, 6 percent per year since 1994. A similar amount is held at other types of financial institutions.[4]

However, data available through the first half of 1998 indicate that 29 rated issues, totaling about $2.6 billion, have been offered either publicly or privately since such securities were first issued in 1992 (Board of Governors, 1998, Exhibit B). Only about $700 million have been marketed since 1996.[5] A few companies, such as The Money Store and Fremont Financial Corporation, have dominated most of the securitizations to date. Several initiatives have been tried, such as, Lori Mae, Inc. and Commonwealth Development Associates, Inc.

According to the Federal Reserve Board, the factors contributing to the relatively slow growth of small business loan securitization are:

- The lack of standardized lending terms
- The lack of uniform underwriting guidelines
- The historical nature of "relational lending"
- The lack of historical data on credit performance

Small business loans lack standardized lending terms and documentation because they are more heterogeneous than home mortgages. Small business loans are extended to many different types of borrowers, and may be secured by various types of business or personal assets.

This lack of standardized loan terms and documents, along with the lack of uniform underwriting guidelines, makes it difficult to evaluate credit risk, to estimate loss-probability distributions, and to project cash flow in underwriting. All the securitizations backed by SBA loans have benefited to some extent from the relatively standardized underwriting guidelines and loan documentation that the SBA requires.

In addition, information-related problems and loan monitoring difficulties are more severe in some respects for small business loans than for home mortgages, other consumer loans, or even commercial mortgages.[6] This is due, in part, to the fact that small business loans involve many different types of businesses with many different characteristics.

In the past, many lenders have been able to overcome their information-related problems with small business lending by establishing long-term relationships with small business borrowers. Likewise, to secure a reliable flow of credit, small businesses usually continue to borrow from the same lender or small group of lenders.

In making these loans, lenders rely on credit reports, financial statements, application information, personal histories, and business judgment to make lending decisions. Over time, some of these lenders might acquire private or confidential information about the borrower that could be helpful in future lending arrangements (Berger and Udell, 1995). In any event, these lending practices tend to be expensive, time-consuming for both lender and borrower, and frequently arbitrary.

However, little of this information about the credit histories of different types of small business loans or borrowers has been systematically compiled or made available to credit rating firms and investors. Therefore, without adequate information or loss-probability distribution of different types of small business borrowers, business loan losses cannot be estimated and, thus, small business loans cannot be securitized.

The related problem is that most lenders do not lend to a specific type of business exclusively. Loans to hotels would have a different collateral structure and probably be subject to different factors affecting repayment than loans to machine-tool businesses, or at least investors think so. Presumably, an advantage of credit scoring is that it would be able to pool loans with similar risk profiles.

Risk Management Systems for Small Business Loans (Section V)

Small business lending has attributes of commercial lending and consumer lending, although it is much more like the latter. On the one hand, small business loans differ from consumer loans in that most consumer-related loans are not expected to generate a repayment stream—instead, repayment depends on other sources of income to the borrower, for example income from employment. On the other hand, both small business and consumer lending generate high volumes of applications, yet involve lower dollar amounts per application than commercial loan applications.

However, the greatest similarity between small business loans and consumer lending is that the creditworthiness of a business is tied to the financial profile of the business' principals, with one caveat. As the size of the business grows, personal information becomes less important and business information becomes more important.[7] When commercial information is available, as it is in the majority of cases, it has more predictive power than consumer information.

Over the past 25 years, credit scoring has become widely used in issuing credit cards and in other types of consumer lending, such as auto loans and home equity loans (Lewis, 1992).

What is new, however, is that small business lending has undergone a revolutionary change over the past few years. The traditional, branch-driven, "relational lending" practices have given way to "knowledge-based" decision making. Operating on a national scale, knowledge-based decision systems now use credit scoring models to enhance efficiency, objectivity, and consistency.

But, what exactly is credit scoring? Credit scoring is a method of evaluating the credit risk of loan applicants. The key objectives of a credit scoring model are to assess risk and to measure the probability of payback in a cost-effective and timely manner. Scoring provides a quick (loan-processing time is reduced from 12 hours to under an hour), accurate risk assessment of applicants, and rank-orders them by the relative amount of risk they represent. Using historical data and statistical techniques, credit scoring tries to isolate the relationship of various applicant characteristics to the potential risk of loan delinquencies and defaults.

As shown in Table 1, the main difference between evaluating a customer based on business judgment alone versus credit scoring is that the credit scored application also predicts the odds of repayment, allowing the lender to rank-order applicants according to the probability of repayment.

The first bank to use scoring for small business lending was Wells Fargo. Wells Fargo was the first large bank that had enough empirical loan data to build a reliable model prior to 1995. Other large banks followed including BankAmerica, NationsBank, Fleet, and Bank One. However, credit scoring has not been available to 'smaller' banks and other lenders who do not have sufficient historical data on which to build their own models.

In March 1995, Fair, Isaac Inc. introduced its "Small Business Scoring Service (SBSS)," scoring models that were developed with Robert Morris Associates, a trade association of commercial lenders. The Fair, Isaac system for scoring small business loans has been purchased by more than 300 lenders. The Fair, Isaac model was built using four years' worth of data on small business loans from 17 banks in the United States, and a sample of more than 5,000 loan applications from businesses with gross sales of less than $5 million.[8]

As Fair, Isaac and the credit scoring banks have discovered, the key to the successful implementation of a risk management decision-making system is to make effective use of the widest possible range of information and to eliminate the information that tends to be unreliable. Prompt payment, change in payment promptness, over utilization of credit, and previous bankruptcy have proven to be the best predictors. On the other hand, information from financial statements—accounts receivable, working capital, net worth, inventory, profits—have proven to be notoriously unreliable and frequently not available for new and small companies.

Another key is having a data integration process for extracting useful information from this body of knowledge. The first step in this data integration process is to assign a unique identifier that can be used to pull together all of the individual data elements pertaining to any single applicant. The next step is to make sure the data are cleaned, and then finally stored in a data warehouse for future use.

A decision system designed to deal with new loan applications is illustrated in Figure 1. However, it is important to bear in mind that no matter how good the credit scoring model, it is only a decision-making tool. It simply provides an assessment of risk. Business judgment still needs to be exercised to arrive at a decision. This ultimate business judgment is based on a combination of scores and decision rules, which specify what actions to take on the basis of the nature of the loan application and the degree of risk associated with it. This process can be largely automated with difficult marginal cases being left to the underwriter.

Finally, state-of-the-art systems allow for the management of the whole credit cycle. This includes not only credit scoring but also tracking the performance of the whole portfolio with respect to frequency of payments and loan default. Portfolio risk assessment should be able to adjust for changing business conditions that affect small businesses. Early warning systems should provide forward-looking assessments of risk that can provide the basis for possible corrective or defensive action on the part of the lender.[9]

In summary, credit scoring has some obvious benefits. First, it reduces costs by increasing the efficiency of the loan process. The cost- and time-savings benefit lender and borrower alike. Second, credit scoring enhances objectivity in the loan process. Third, and perhaps most important in terms of securitization, it is a method for evaluating risk and probability of loan repayment.

Nevertheless, credit scoring has some limitations. For one, the accuracy of the scoring system for underrepresented groups is still an open question (Padhi and Woosley, 1999). The issue is whether credit scoring produces discriminatory results because of the under representation of minority groups. The short answer should be that credit scoring ought to be color-or ethnicity-neutral. The model does not know the race of the borrower. But, this is a somewhat controversial issue, as some charge that certain credit scoring results can be assessed in a manner which produce poor scores for “disadvantaged” businesses. Second, the models have not been tested on larger loans. Only a few banks are using the models for loans over $50,000, and none is using the models for loans over $100,000.[10]

Third, the experts are confident that the models rank-order risk. In fact, they do. A business loan seasons in 3–4 years, so to the extent lenders started using credit scoring four years ago, we are coming up to the point where preliminary judgements can be made on the utility of the model as the loans are seasoned. The loss rate on portfolios of scored loans has been less than twenty-five basis points.

While the models are able to rank-order risk, it is probably too soon to determine the accuracy of small business credit scoring during an economic downturn since the models were developed after the last recession in 1991. However, even SBA- guaranteed loans, which are riskier on average than non-SBA guaranteed loans, performed very well during the 1991 recession.

Analysis (Section VI)

While credit scoring has overcome some of the most serious limitations of small business lending—the lack of standardized lending terms and uniform underwriting guidelines—the rate of securitization of small business loans has not increased over the same time period.

Most large banks use credit scoring models to evaluate their small business loans today. It is estimated by industry sources that almost one half of all small business loans are credit scored. The Fair, Isaac model alone is used by over 300 banks. However, while many of the larger banks use scoring models, most of the smaller community banks do not. Most community banks do not have the volume of business to justify using scoring models, and therefore rely on conventional judgmental methods to evaluate small business loans.

Why have the larger banks, which are using scoring models, not securitized more of their small business loans? One frequently cited reason is liquidity. Banks balance sheets are in better shape than at any other time in this decade. The reasons for increased bank liquidity are a low inflation rate, the elimination of the Federal budget deficit, and the increased use of securitization by banks. Therefore, the Federal Reserve has maintained a relatively easy monetary policy. Bank managers have not found it necessity to securitize small business loans to reduce interest rate risk. For other loans, the infrastructure for securitization already exists.

If larger banks wanted to securitize small business loans they have the technical expertise, and the institutional infrastructure to do so. However, for community banks, that is not the case. For example, while the infrastructure for securitizing home mortgages is well established, there exists no comparable infrastructure to securitize small business loans. The only exception is for SBA guaranteed loans where SBA regulations have established a framework with a fiscal agent for securitizing these loans.

The Riegle Act was not intended to create an active role for the federal government in the form of subsidies or credit guarantees, such as the explicit and implicit guarantees provided by the government sponsored enterprises like Fannie Mae and Freddie Mac. Thus, issuers of securities backed by small business loans must look for alternative forms of credit enhancement, to qualify for high credit ratings, required to market senior securities.

Recently, a startup company called Lori Mae Inc. in Portland Oregon, attempted to create a program to securitize small business loans originated by community banks.[11] It wanted to acquire scored small business lines of credit and package them for securitization. However, the response from community banks was less than desired, and Lori Mae was unable to complete the program. The company is repositioning its program and may return to the market later this year.

The results of the Lori Mae initiate have important lessons for the development of secondary markets. First, many of the community banks—like larger banks—do not have a liquidity problem, do not have the opportunity to make additional small business loans, are loosing money on existing small business loans, or are concentrating on other issues—like the Y2K problem. Second, the spreads on small business loans are frequently so narrow that the costs to securitize may offset the marginal benefits. Third, many community banks are motivated by growth and will not pursue strategies that compete with that goal.[12]

In sum, at this time, securitization of small business loans does not appear to appeal to either large-or small-banks. While credit scoring appears to be necessary for securitization, it is not sufficient. It does not appear that the increased use of credit scoring models to underwrite small business loans will lead to an increase in the securitization of small business loans as had been suggested by the Board of Governors of the Federal Reserve System (1998).

In the final analysis, it appears that the development of a secondary market for small business loans may not materialize until the macroeconomic conditions change.[13]

Conclusions (Section VII)

In 1994, Congress passed The Riegle Act to remove regulatory obstacles to the securitization of small business loans. The Act extended to securitized small business loans the same benefits extended to residential mortgage-backed securities.

Notwithstanding, the market for securitized small business loans—separate and apart from SBA-guaranteed loans—appears to be developing more slowly than other asset-backed securities.

This study concludes that one reason cited for the slow growth is the limited amount of information available on credit performance of small business loans—assessing credit risk is a major obstacle to the development of small business loan securitizations. In addition, securitizations have moved slowly because small business loans have disparate qualities.

The study also found that a major category of originators—community banks—are not interested, particularly in the current macroeconomic environment. Current economic conditions—where everyone is flush and liqudity is less of an issue—create less demand for securitizations, as lenders are less inclined to seek relief from interest rate risk.

In sum, the study found no information suggesting that slow securitization is regulatory in nature or anything other than market-driven. Consequently, recommendations endorsing new programs or government regulations do not seem merited.

Under the Act, the Federal Reserve Board is required to issue one more report next year on small business loan securitizations. This study identifies several aspects of the issue that merit further analysis by the Federal Reserve Board when preparing its report.

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TABLE 1

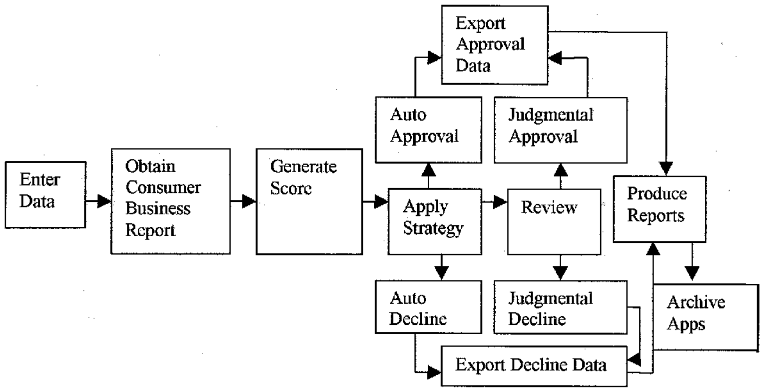
Evaluating the Business Applicant

Characteristic	Judgment	Credit Scoring
Years in Business	+	56
SIC Code	-	52
Debt/Worth	+	25
Cash/Total Assets	Neutral	43
Principal Income	-	30
CB Score	-	–2
# of Inquiries	+	–7
% Satisfactory	+	5
# Of Derogs on Business Report		10
Overall	+	212
Decision	Accept	Accept
Odds of Repayment	?	40:1

Source: Fair, Isaac and Company, Inc.

FIGURE 1

Automated Application Processing



Source: Fair, Isaac and Company, Inc.

EXHIBIT A

Growth of Small Business Loans at U.S. Commercial Banks[1] (Billions of Dollars)

Year	Total Business Loans	Commercial and Industrial Loans	Non-farm, Non-residential Real Estate Loans
1993	295.0	157.2	137.8
1994	294.2	154.5	139.7
1995	315.9	165.3	150.7
1996	333.1	175.8	157.3
1997	357.6	196.1	161.5
1998[2]	370.8	197.2	173.6

1. Business loans of $1 million or less at U. S. domestically chartered commercial banks, excluding U.S. branches and agencies of foreign banks. U. S. branches and agencies of foreign banks held approximately $178 billion of commercial and industrial loans on June 30, 1998, almost all of which were greater than $1,000.000.
2. Preliminary.

EXHIBIT B

Rated Offerings of Securities Backed by Small Business Loans[1] (Volume in Millions of Dollars)

Year	Number	Volume
1992	2	574.0
1993	3	376.3
1994	3	201.9
1995	4	211.9
1996	7	530.0
1997	8	489.1
1998[2]	3	212.9
Total	29	2596.1

1. Includes securities backed by the unguaranteed portion of SBA loans, *but excludes those backed by the guaranteed portion.*

2. Includes data through July 1998.

Source: Moody's, SBA, as cited in Board of Governors of the Federal Reserve System, 1998, p. 38.

EXHIBIT C

Small Business-Loan Securitizations Since Mid-1996 (Rated Offerings)

Issuer(series)	Issue date	Amount ($million)	Collateral type	Credit enhancement Amount (Percent)	Credit enhancement Type	Class	Credit Rating
Emergant Business Capital (1996-1)	11-96	17.5	Unguaranteed portions of SBA loans	9.0	Subordination		
				6.0	Spread Account		
		15.9				A	Aa
		1.6				B	n.r
The Nancy Store	12-96	140.0	Unguaranteed portions of SBA Loans	7.0	Subordination		
				3.5	Spread Account		
		130.2				A	Aaa
		9.8				B	A
The Money Store	3-97	90.0	First mortgages secured by commercial real estate associated with 504 and 7(a) loans	8.0	Subordination		
				3.5	Spread Account		
		75.6				A	AAA
		7.2				M	AA
		7.2				B	BBB
Fremont Financial	4-97	109.3	Small business loans	9.0	Subordination		
		100.0				A	AAA
		9.3				B	BBB
Sierra West (1997-1)	6-97	51.3	Unguaranteed portions of SBA Loans	7.0	Subordination		
				4.0	Spread Account		
		47.7				A	Aaa
		3.6				B	A
The Money Store	9-97	140.0	Unguaranteed portions of SBA Loans	7.0	Subordination		
				3.5	Spread Account		
		130.2				A	AAA
		9.8				B	A
Independence Funding (1997-1)	11.97	34.3	Unguaranteed portions of SBA Loans	10.0	Subordination		
				4.0	Spread Account		
		30.9				A	Aaa
		3.4				B	A

n.r. Not rated

EXHIBIT C (CONTINUED)

Issuer(series)	Issue date	Amount ($million)	Collateral type	Credit enhancement Amount (Percent)	Credit enhancement Type	Class	Credit Rating
First Western(1997-1)	12-97	22.6	Unguaranteed portions of SBA loans	7.0	Subordination		
				6.0	Spread Account		
		21.2				A	Aaa
		1.6				B	A
Business Loan Center (1997-1)	12-97	19.9	Unguaranteed portions of SBA Loans	9.0	Subordination		
				4.0	Spread Account		
		16.1				A	Aaa
		1.6				B	n.r.
Emergent Business Capital (1997-1)	12-97	21.5	Unguaranteed portions of SBA loans	10.0	Subordination		
				6.0	Spread Account		
		19.4				A	A
		2.2				B	n.r.
The Money Store(1998-1)	3-98	90.0	Unguaranteed portions of SBA loans	7.0	Subordination		
				3.5	Spread Account		
		83.7				A	Aaa
		6.3				B	A
Heller First Capital (1998-1)	6-98	96.0	Unguaranteed portions of SBA Loans	4.0	Subordination		
				2.0	Spread Account		
		75.9				A	Aaa
		6.7				M-1	AA
		3.8				M-2	A
		5.8				M-3	BBB
		3.8				B	BB
First National Bank of New England(1998-1)	6-98	26.9	Unguaranteed portions of SBA Loans	10.0	Subordination		
				7.0	Spread Account		
		24.2				A	AAA
		27.0				B	n.r.

n.r. Not rated

Notes

1 A similar set of issues was faced in the creation of the angel-capital market (Acs and Tarpley, 1998).

2 Board of Governors of the Federal Reserve System, September 1998, Exhibit 13 and 14, p. 38.

3 The entity can be either a trust, a partnership or a corporation.

4 The percentage of these loans that are credit scored is unknown. However, banks with over $5 billion in assets make about half of the small business loans (defined as loans of less than $1 million).

5 Limitations on the development of a secondary market for small business loans do not appear to be regulatory in nature.

6 The importance of adequate information on credit risk is demonstrated by the fact that, over the past eleven years, when small business loans have been backed by a federal guarantee to repay interest and principal, upwards of 50 percent of SBA loans have been securitized.

7 The threshold for most consumer credit scored models is $250 and for commercial usage it is $1,000. Most commercial models are applied to business loans of under $50,000.

8 Other companies, such as CCN-MDS, Dun & Bradstreet and Experian (formerly TRW), are developing or already have developed competitive products. However, none has developed models that incorporate both application information and financial statement information, both of which are part of standard lending practice.

9 The move to credit scored, small business lending makes banks more likely to be targeted by fraud professionals. This is due, in part, to the fact that each transaction gets less attention, and banks are less likely to know their customers. However, the system can provide for a fraud model as part of an effective risk management system.

10 The next generation of models now being developed will have the capability of scoring larger loans.

11 A similar effort is currently underway by Commonwealth Development Associates, Inc.

12 One other lesson emerges from the Lori Mae experiment. While community banks may not be interested in securitizatizing small business loans, they are very interested in Community Reinvestment Act (CRA) credits. In other words, if community banks would receive CRA credits they would be interested in securitizing small business loans. However, one obstacle to this is that most small business loans that would qualify for CRA credits cannot pass credit scoring.

13 Also see Harrington and Yago, 1999, for a policy discussion on the role of securitization in funding minority business.

References

Acs, Z.J. and F.A. Tarpley. “The Angel Capital Electronic Network,” in Special Issue on The Economics of Small-Business Finance, edited by A.N. Berger and G.F. Udell, *Journal of Banking and Finance*, 22:6-8, 1998, pp. 793-797.

Allen, J.C. “Small business Banking: A Promise of Approvals in Minutes, Not Hours,” *American Banker*, February 28, 1995.

Asch, L. “How the RMA/Fair, Isaac Credit scoring Model Was Built,” *The Journal of Commercial Lending*, June 1995, pp. 1-7.

_______. “Credit Scoring: A Strategic Advance for Small Business Banking,” *Commercial Lending Review*, 1997, pp. 18-23.

Berger, A.N. and G.F. Udell. “Relationship Lending and Lines of Credit in Small-Firm Finance,” *Journal of Business*, 68, 1995, pp. 351-382.

_______. Editors, “The Economics of Small Business Finance,” *Journal of Banking & Finance*, 22, 1998, pp. 6-8.

Beshouri, C. and P. Nigro. “Securitization of Small Business Loans,” Economic and Policy Analysis, Working Paper 94-8, Comptroller of the Currency, December 1994.

Board of Governors of the Federal Reserve System. *Report to the Congress on Markets for Small Business- and Commercial-Mortgage-Related Securities*, Washington, D.C., September 1996.

_______. *Report to the Congress on Markets for Small Business- and Commercial-Mortgage-Related Securities*, Washington, D.C., September 1998.

Eisenbeis, R.A. “Recent Developments in the Application of Credit Scoring Techniques to the Evaluation of Commercial Loans,” paper presented at the Conference on Credit Scoring and Credit Control IV, Edinburgh University, Management School, September 7, 1995.

Feldman, R. “Will the Securitization Revolution Spread?,” *The Region*, Federal Reserve Bank of Minneapolis, Minnesota, September 1995, pp. 23-30.

Harrington, M. and G. Yago. “Mainstreaming Minority Business,” Policy Brief, Milken Institute, Santa Monica, California, February 1999.

Kendall, L.T. and M.J. Fishman, 1998, *A Primer on Securitization*, The MIT Press, Cambridge, Massachusetts.

Kerlionger, F. *Foundations of Behavioral Research*, 3rd edition, Holt Reinhart & Winston, San Francisco, California, 1986.

Kresge, D.T. “Risk Management Systems for Small Business Loans,” Dun & Bradstreet Corporation, July 16, 1998.

Lewis, E. M. *An Introduction to Credit Scoring*, The Athena Press, San Rafael, California, 1992.

Lori Mae Inc. Program Description, Portland, Oregon, 1998.

Mester, L.J. “What’s the Point of Credit Scoring?,” *Business Review*, Federal Reserve Bank of Philadelphia, Pennsylvania, September/October 1997.

Moody's Investors Service. "The Impact of Interim SBA Regulation on 7(a) Unguaranteed Loan Securitization," Special Report, October 31, 1977.

Oppenheim, J. "Would Credit Scoring Backfire in a Recession?," *American Banker*, 16, November 18, 1966.

Padhi M.S. and L.W. Woosley. "Credit Scoring and Small Business Lending in Low- and Moderate-Income Communities," this volume.

Rutherford, R. "Securitizing Small business Loans: A Banker's Action Plan," *Commercial Lending Review*, 10:1, Winter, 1994-95.

Schaltzman, L. and A.L. Strauss. Field Research: *Strategies for a Natural Sociology*, Prentice Hall, Englewood Cliffs, New Jersey, 1973.

Shear, W. B. "Economic Studies by Four Agencies on the Benefits and Costs of Government Sponsorship of Fannie Mae and Freddie Mac," University of Pennsylvania. 1996.

Strategic Research Institute Conference. *Credit Scoring*, Roosevelt Hotel, New York, New York, September 23-24, 1998.

U.S. Department of Housing and Urban Development. Office of Policy Development and Research, *Studies on Privatizing Fannie Mae and Freddie Mac*, Washington, D.C., May 1966.

U.S. General Accounting Office. Housing Enterprises: Potential Impact of Severing Government Sponsorship, Washington D.C., May 1966.

U.S. Small Business Administration. *Independent Study of (7a) and 504 Loan Programs*, prepared by Walker and Company, 1997.

Walker, D.T. "Dealing With Risk-Based Pricing," *Mortgage Originator*, August 1998, pp. 18-35.

Credit Scoring and Securitization of Small Business Loans

Discussion Comments
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Introduction

This session features two papers. One paper discusses the potential for credit scoring to facilitate the growth of securitization of small business loans. The other paper provides empirical evidence on the possible effects of credit scoring on lending to businesses in low-and moderate-income areas.

Credit Scoring and Securitization

In "Development and Expansion of Secondary Markets for Small Business Loans," Zoltan Acs discusses the potential market for securitization of small business loans. At present, he notes, very little small business credit has been securitized. He attributes the low volume of small business securitization to a lack of standardized lending terms, a lack of uniform underwriting standards, and a lack of historical data on payment performance. Pointing to similarities in small business lending and consumer credit, he argues that promotion of credit scoring for small business lending decisions would stimulate further development of historical data on payment performance. This development would, in turn, lead to relatively greater securitization of small business credit.

The observation that consumer credit and small business lending have many similarities is important. By far most small businesses are very small. Over three-fourths of small businesses had assets of less than $500,000 according to the 1993 National Survey of Small Business Finances (Cole and Wolken, 1995). The amount of credit that these small businesses use is also very small. Thus, small business lending is characterized by a relatively large number of requests for small amounts of credit, making it sensible to treat the small loan product as a standardized product (like consumer loans) rather than a customized product (like traditional commercial loans). Such treatment, of course, would produce greater standardization of small business lending terms, which would be favorable to securitization of small business loans. Such treatment would also reduce the operating cost of lending to small businesses.

Lack of information is a critical problem in small business lending. This problem has caused small businesses to rely heavily on relationship lending in the past. Acs notes that the creditworthiness of a business is tied to the creditworthiness of its owners. Owners' personal credit histories are useful for predicting performance on business loans and are readily available. Still, few creditors are willing to rely solely on the personal credit histories of business owners. Many creditors have begun to use credit scoring models that combine data on owners and businesses. Credit scoring models that combine data on owners and businesses perform better than models that use only owner data or only business data (Daly, 1995). All of the three large consumer credit bureaus offer services that combine credit information on business owners and businesses. These services will provide necessary data for further development of credit scoring models for small business lending. Importantly, these services will make credit scoring available to smaller creditors, who may not have sufficient historical data on which to build their own credit scoring models for small business lending.

The paper could make a stronger case for credit scoring in small business lending. Credit scoring has important strengths in the way information is used when compared with alternative judgemental credit evaluation methods (Chandler and Coffman, 1979; Eisenbeis, 1980). Some of the limitations mentioned for credit scoring are also problems for judgemental credit evaluation methods. Several points are worth noting.

First, credit scoring models economize on the use of information. They make better use of available information than judgemental credit evaluation methods by considering intercorrelations among the different pieces of information. They are also better able to eliminate redundant information. Thus, credit scoring models generally require less information than judgemental credit evaluation methods to make a decision. Small businesses may more easily be able to satisfy the information requirements for a credit scoring model than for a judgemental credit evaluation.

In addition, credit scoring models consider more of the available information than judgemental credit evaluation methods. Credit scoring models are developed using large random samples of good and bad accounts. Judgemental credit evaluation methods, in contrast, are rarely based on large random samples of past good and bad accounts. Judgemental evaluations are typically based on an individual analyst's experience of account performance, augmented by his perceptions of the prior experience of other lenders. They are subject to imperfect recollection and experience based on a limited and nonrandom sample. Moreover, judgemental methods tend to focus heavily on bad accounts that have been approved in the past, as they are the exceptions that have been brought to the attention of the analyst. Thus, judgemental evaluation methods tend to ignore a substantial quantity of available information.

The paper mentions a concern of some individuals that credit scoring models may not reflect the creditworthiness of certain types of applicants who in the past have not been well represented among borrowers. They argue that credit scoring may perpetuate past lending decisions, making it more difficult for those types of applicants to obtain credit. A concern about perpetuating past decisions is warranted, but the concern applies to any method of credit evaluation that is based solely on creditors' experience with approved accounts. With credit scoring, statistical methods exist to adjust (albeit, imperfectly) for bias. Statistical methods fail completely only if there is no overlap between accepted applicants and underrepresented rejected applicants. Even without adjustment, a credit scoring system will generally accept some of the underrepresented group and, therefore, tends to correct for past biases. In a judgemental system, correcting for past biases is very difficult if not impossible. Since most judgemental systems focus on bad accounts rather than both good and bad accounts, and since there is virtually no way to adjust for the absence of information regarding previously rejected applicants or underrepresented groups, the judgemental system is more likely to perpetuate past biases than credit scoring models.

Credit scoring models may provide greater possibilities than judgemental methods for credit applicants to compensate for weaknesses in evaluated characteristics and, thereby, obtain credit. Credit scoring models are based on a multivariate statistical analysis, which assigns the appropriate weights given the impact of other characteristics. These weights allow strengths in one characteristic to compensate for weaknesses in others. In judgemental credit evaluation, it is virtually impossible for the credit analyst to consider simultaneously all of the relevant information that may be related to creditworthiness. Judgemental evaluation is likely to assign too much weight on an individual characteristic and not enough weight on other characteristics. Weights may be assigned to characteristics based on local "folklore," and as mentioned, weights are likely to be based on characteristics of known bad accounts rather than characteristics that distinguish between good and bad accounts. Under such circumstances, an applicant having a characteristic that is associated with known bad accounts may have difficulty persuading a credit analyst that strengths in other areas compensate for this weakness.

My last point in this section concerns the lack of evidence on the performance of small business credit scoring models during a downturn in the economy. This limitation is a consequence of the relatively recent use of credit scoring for small business lending. It is likely to be a transitory problem. Also, judgemental credit evaluation methods are not free of this problem. Many credit analysts do not have experience with a downturn in the economy, and others may not remember very accurately the previous downturn.

Empirical Evidence on the Effect of Credit Scoring on Small Business Lending

For "Credit Scoring and Small Business Lending in Low- and Moderate-Income Communities," Michael Padni, Aruna Srinvasan, and Lynn Woosley created a database on small business lending using information collected under the Community Reinvestment Act, information of use of credit scoring from an in-house survey, and geographic information from other sources. The data cover large banks in urban areas of states in the Atlanta Federal Reserve district. The paper presents descriptive statistics comparing extensions of small loans by scoring and non-scoring banks in census tracts that are characterized by different levels of income. The paper also presents results of regression analyses designed to ascertain the effects of credit scoring on extensions of small loans holding other factors constant. The evidence suggests that credit scoring is associated with greater lending overall and in low-income tracts. The evidence on lending in moderate-income census tracts is less clear.

A good empirical study requires good data. The authors of this paper took care in constructing the database. They corrected for missing data where they could, and they analyzed the consequences of reporting errors in the Community Reinvestment Act data. These efforts give one confidence in the data used in the statistical analyses. A few details in documenting the data were overlooked, however. Missing is a discussion of the relative frequency and any distinguishing characteristics of census tracts excluded because of missing Dun & Bradstreet small business data. Also missing is a discussion of any distinguishing features of the 48% of large banks that did not respond to the in-house survey asking about the banks' use of credit scoring. Some uncertainty about the representativeness of the data remains without some discussion of these matters.

The paper obviously presents preliminary results and should be judged accordingly. The most important need is greater explanation and development of the empirical model. The paper is weak in this area, even for a preliminary paper. For example, one regression model is estimated for all small business loans in the region. A second model is estimated using separate regressions for each state in the region and including observations with zero loan amounts. The second model apparently is the result of an unexpected finding for one of the explanatory variables together with an inability to estimate a single equation for the entire region when observations with zero loan amounts are included. There is little discussion of the underlying decision processes that helps one choose between the two models, however. The underlying decision processes are also important for choosing an appropriate limited dependent variable technique for the second model, which the authors note is needed. In addition, further discussion and justification is needed for the variables used in the regression model. The paper simply lists the explanatory variables. It does not discuss whether a variable represents a supply or demand factor or explain the variable's relationship to the dependent variable. A few variables are listed with no explanation at all. In sum, the paper provides very little guidance on the model. Improvements in this area would greatly increase the credibility of the empirical results.

Conclusions

In summary, these papers make a good case for encouraging use of credit scoring in small business lending. The first paper provides a summary of the benefits of securitization and argues convincingly that credit scoring can reduce the cost and facilitate securitization of small business lending. The second paper provides needed empirical evidence on credit scoring's effect on the volume of small business lending. This empirical evidence supports the hypothesis that credit scoring is associated with a greater volume of small business lending. The evidence also suggests that credit scoring is associated with greater small business lending in low-income areas.

It is notable that for other credit products, growth in credit scoring and securitization coincided with an expansion of credit among low- and moderate-income customers. This is particularly evident for bank credit cards. Nearly 25 years ago, about a third of U.S. households had bank credit cards (Durkin and Elliehausen, 1978). Credit scoring was relatively new, and securities backed by credit card receivables were not publicly available. Bank credit card ownership was heavily concentrated in higher income households at that time. Few low-income households had bank credit cards. Bank card ownership increased to 56% of households in 1989 and to 67% of households in 1995 (Kennickell, McClure and Sunden, 1997). Credit scoring became common for evaluation of credit card applications during this period, and the percentage of revolving credit (which was mostly credit cards) that was securitized increased from 6% in 1989 to about 32% in 1995. Coinciding with the rise in credit scoring and securitization was a dramatic increase in bank card ownership among low- and moderate-income households. Among households with incomes less than $10,000 (in 1995 dollars), for example, bank credit card ownership increased 80%, from 15% of households in 1989 to 26% of households in 1995. Among households with incomes of $10,000 to $24,999, bank credit card ownership increased 55%, from 34% in 1989 to 53% in 1995. Considering the reductions in cost and risk from credit scoring and securitization of credit cards, the spread of bank credit card ownership to lower income households is not likely coincidental.

As mentioned, credit scoring of small business lending has begun to take hold. Further expansion of credit scoring should stimulate small business lending and facilitate securitization. Experience in the bank credit card market suggests that small businesses in low- and moderate-income areas are likely to share the benefits of these developments.

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References

Chandler, Gary G. and John Y. Coffman. "A Comparative Analysis of Empirical vs. Judgmental Credit Evaluation," *Journal of Retail Banking*, 1:2, September 1979, pp. 15-26.

Cole, Rebel A. and John D. Wolken. "Financial Services Used by Small Businesses: Evidence from the 1993 National Survey of Small Business Finances," *Federal Reserve Bulletin*, 81:7, July 1995, pp. 629-667.

Daly, James J. "Risky Business Cards," *Credit Card Management*, 8:9, September 1995, pp. 114-119.

Durkin, Thomas A. and Gregory Elliehausen. 1977 *Consumer Credit Survey*, Board of Governors of the Federal Reserve System, Washington, 1978.

Eisenbeis, Robert A. "Selection and Disclosure of Reasons for Adverse Action in Credit-Granting Systems," *Federal Reserve Bulletin*, 66:9, September 1980, pp. 727-735.

Kennickell, Arthur B., Martha Starr-McClure, and Anniko Sunden. "Family Finances in the U.S.: Recent Evidence from the Survey of Consumer Finances," *Federal Reserve Bulletin*, 83:1, January 1997, pp. 1-24.

Credit Scoring and Securitization of Small Business Loans

Discussion Comments
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Both papers, "Credit Scoring and Small Business Lending in Low- and Moderate-Income Communities," by Michael S. Padhi, Lynn W. Woosley, and Aruna Srinivasan (1999), and "Development and Expansion of Secondary Markets for Small Business Loans," by Zoltan Acs (1999) are positive about credit scoring. The Padhi, et al. (1999) paper asks whether large banks that use credit scoring for small business loan originations do less lending in low- and moderate-income areas than banks that do not use credit scoring. For low-income tracts, the paper finds just the opposite: that the scorers do *more* lending in these tracts than the nonscorers. The Acs (1999) paper argues that credit scoring will enable securitization of small business loans and therefore, should be encouraged, since securitization means more funds will be available to small businesses, as we've seen in the mortgage markets. Thus, both papers argue that the technological change of credit scoring will result in more funding going to small businesses.

What I'm going to argue is that (1) we might see more funding going to small businesses, but (2) the *nature* of that funding will be different, and (3) various forces, including credit scoring, but not exclusively credit scoring, are leading to this change in the nature of lending. Finally, (4) there will be a new equilibrium with some small businesses going to scorers and other small businesses going to nonscorers for their funding, but (5) the transition to this new equilibrium may not be painless.

Why do we need the empirical investigation of the new technology now? Because more and more banks are beginning to use credit scoring for small-business loans. According to a survey of 150 banks reported in the *American Banker* in May 1995, only 8 percent of the respondents with up to $5 billion in assets used scoring for small-business loans, while 23 percent of larger banks did. (55 percent of banks with more than $5 billion in assets reported they planned to

The views expressed here are those of the author and do not necessarily represent those of the Federal Reserve Bank of Philadelphia or of the Federal Reserve System.

implement scoring in the next two years.) In the January 1997 Senior Loan Officer Opinion Survey on Bank Lending Practices, which surveys larger banks, 70 percent of the respondents (i.e., 38 banks), indicated they use credit scoring in their small-business lending, and 22 of these banks said they usually or always do so. The Padhi, et al. (1999) paper surveyed the 200 largest banks in January 1998 and found that 63 percent of the respondents used credit scoring for small-business loans and an additional 11 percent planned to by June 1999. Generally, all the banks that are using scoring are doing it for loans less than $100,000.

Mester (1997) reviewed some of the benefits and limitations of credit scoring. First let's examine the benefits. Scoring holds the promise of offering a quicker, cheaper, more objective loan application approval process. A study by the Business Banking Board found that the traditional loan approval process averages about 12.5 hours per small-business loan; credit scoring can reduce this time to well under an hour. This time savings benefits the customer as well as the bank, since the applicant only has to provide information used in the scoring system. Before CoreStates was acquired by First Union, it was planning an automatic loan approval process based solely on a credit score for loans of $35,000 and under—the application was half a page long and no financial statements were required. For many banks the scoring systems, themselves, are not prohibitively expensive, averaging $1.50 to $10 per applicant, depending on the volume. The bank can allocate its credit evaluation resources more efficiently by allowing loan officers to concentrate on the less clear-cut cases. Another benefit is improved objectivity in the loan approval process. Scoring helps lenders ensure that they are applying the same underwriting criteria to all borrowers regardless of race, gender, or other factors that the law prohibits from being used in credit decisions. The scoring model makes it easier for a lender to document the business reason for using a factor that might have a disproportionately negative effect on certain groups of applicants protected by law from discrimination.

But there are several limitations of scoring, which I believe need some emphasis. Some of these limitations lead me to believe that the transition to a new equilibrium, which I'll discuss later, will not necessarily be painless. First, the scoring model is only as good as the data with which it was built. This seems obvious, but it does have some important implications. The first banks to use scoring for small-business loans were larger banks that had enough historical loan data to build a reliable model. These banks included Hibernia Corp., Wells Fargo, BankAmerica, Citicorp, NationsBank, Fleet, and Bank One. BankAmerica's model was developed based on 15,000 good and 15,000 bad loans, with face values up to $50,000. The reason credit scoring is now available to lenders who do not have sufficient volumes to build their own models is that Fair, Isaac and

Co., in collaboration with RMA, a trade association of commercial lenders, pooled five years' worth of data on small-business loans from 17 banks in the U.S. They created a sample of more than 5,000 loan applications from businesses with gross sales of less than $5 million and loan face values up to $250,000.

It's also important to remember that the scoring model will reflect the loan performance of borrowers that were well represented in the loan data used to build the model. Some argue, for example, that low- and moderate-income individuals are not well represented in the loan data, since they have been credit rationed in the past. If so, then the scoring models might well be less accurate predictors of *their* loan performance. Of course, this doesn't have to be the case. A study by Fair, Isaac indicated that their scoring model for installment loans was as predictive for low- to moderate-income loan applicants as for the entire sample of applicants, although the low-income subsample had lower scores. And Freddie Mac says its Loan Prospector scoring system is equally predictive of loan performance, regardless of borrower race or income. Related to the question of underrepresented borrowers is possible selection bias. Account should be taken not only of the characteristics of borrowers who were granted credit but also of those who were denied credit. For example, suppose owning a home means a person is less likely to default on a loan. Then if the majority of applicants that a bank approves are home owners, the distribution of home ownership in the approved applicant pool will differ from that in the total applicant pool. If this fact is ignored in estimating the model, the model could not accurately uncover the relationship between home ownership and loan default. The model would show that home ownership is less predictive of good performance than it actually is. (Note that the Fair, Isaac-RMA scoring model did use data on good and bad loans and denied applications.) Similarly, if a bank using scoring increases its applicant pool by mass marketing, it must ensure that the new pool of applicants behaves similarly to the pool on which the model was built. Otherwise, the model may not accurately predict the behavior of these new applicants.

We've started our ninth year of economic growth. One might think that this is unambiguously a good thing. But for builders of scoring models it's a problem. A good model needs to make accurate predictions in good economic times and bad, so the data on which the model is based should cover both expansions and recessions. Model testing should be done using loan samples that were not used to develop the model in the first place. But even this testing is tricky—if the loan performance in the period from which the testing data were drawn reflects a lot of unsystematic risk factors rather than systematic risk factors, then it might lead the tester to conclude the model was poor, rather than it being just that the loan performance in the testing period is not predictive of future loan performance.

I believe it is too soon to determine the accuracy of small-business loan scoring models because they are fairly new, and we have not been through an economic downturn since their implementation. Also, it is not at all clear that credit scoring models can pick up a firm whose condition is rapidly deteriorating. Thus, lenders will still have to monitor borrowers, so the cost savings from scoring may be overstated. Also, as the world changes, the accuracy of the models will change as well. They will have to be reestimated as more history passes. Newer techniques, like neural networks, do hold some promise of alleviating some of these problems, but they have drawbacks too—e.g., they may suffer from over-fitting problems, so that they fit well in-sample but not out of sample; and the transformations of the variables that are found to be predictive might have little economic meaning.

The evidence on the accuracy of the models in the U.S. is mixed. Some studies have shown the models are fairly accurate in predicting loan performance. A Freddie Mac study of hundreds of thousands of Freddie Mac mortgage loans originated over several years and selected from a wide distribution of lenders, product and loan types, and geographic areas found a high correlation between the scores and loan performance and a high correlation between underwriters' judgments and the Fair, Isaac mortgage credit scores. A study by Avery, Bostic, Calem, and Canner (1996) also found that credit scores based on the credit history of mortgage applicants generally were predictive of mortgage loan performance and added value—credit scores were much stronger predictors of foreclosure than was income. But according to the November 1996 Senior Loan Officer Opinion Survey, 56 percent of the banks that used credit scoring in the credit card operations reported that their models failed to accurately predict loan-quality problems by being too optimistic. The model did not catch the "regime shift" to a world in which declaring personal bankruptcy had less stigma attached to it.

The other thing to remember is that there can be two types of errors. Some applicants will be granted credit but ultimately default. This visibly hurts the lender's bottom line. But other borrowers won't be granted credit even though they would have repaid. This is less visible, but it also hurts the lender's profitability. No scoring model can eliminate these types of errors, but a good model should be able to accurately predict the average performance of loans made to groups of individuals who share similar values of the factors identified as being relevant to credit quality.

Two other potential problems need to be overcome by lenders using credit scoring. First, customers don't seem to like it. (Check out the web site http://www.creditscoring.com/letters/equifax.htm for some interesting reading.) Second, a banker told me that while he's concerned about the accuracy of the scoring models used in his automated loan system, what really keeps him up at night is the thought of a system failure: when an automated loan system goes down, the bank's lending operation is out of business. This means backup systems are important, and of course, this redundancy will raise the costs of automated loan systems.

Against this backdrop of benefits and limitations of scoring, the Padhi, et al. (1999) paper notes that large banks devote a smaller portion of their loan portfolio to small-business loans, perhaps because they find these loans less profitable than their other products. But technological advances, like credit scoring, can lower the marginal costs of originating small-business loans. And this might increase small-business lending.

First, I think it is important to recognize that while it is true that small-business loans represent a smaller proportion of a large bank's loans, large banks do a substantial amount of lending to small businesses. In 1994, banks with assets over $10 billion made over a fifth of the industry's small business loans (while making nearly half of all business loans) (see top panel of Figure 1). In 1998, the large banks made an even greater share—over a third—of the industry's small-business loans (see bottom panel of Figure 1). This partially reflects the industry's shift toward larger banks. It is true, however, that small-business loans make up a smaller share of a large bank's business lending than of a small bank's business lending (see Figure 2). Just in terms of lending capacity, the smallest banks are unable to make many large loans. The ratio of small-business loans to total loans falls from about 95 percent for the smallest banks to less than 20 percent for the largest banks.

The Padhi, et al. (1999) paper asks whether credit scoring will change this picture. In particular, the authors present two types of evidence using a rich and well-constructed data set; they should be congratulated in putting together such an interesting data set. It includes census tract data, the CRA data on small business loans, and their own survey data on the 200 largest banks.

The first type of evidence presented addresses the following questions: Holding "demand" (i.e., business activity) constant, do scorers make more of their loans in high-income tracts or in low-income tracts? Holding "demand" constant, do nonscorers make more of their loans in high-income tracts or in low-income tracts? Then they replicate this for moderate-income tracts, and they also replicate the entire exercise for in-market lenders and out-of-market lenders. Two things emerge: nonscorers distribute their loans fairly evenly across low-income and high-income tracts; credit scorers do not. Except in weak demand tracts (i.e., in tracts where the volume of small-business loans to small-business revenue is less than half a percent), scorers distribute more of their small-business lending to low-income tracts than to high-income tracts. Note that this refers to the share of a bank's loans and not the total volume.

Their next set of results is based on regressions. Here the authors address a different question, namely, do scorers lend more in low- and moderate-income tracts than do nonscorers. Notice that now we are looking at the absolute volume of lending, rather than how a particular bank distributes its loans across tracts. I'm not necessarily convinced by these results. The only variable in the regressions that is a bank characteristic is whether the bank uses credit scoring. Thus, this variable is doing an awful lot of work here. For example, we know that larger banks have been using credit scoring longer than smaller banks, so credit scoring is likely to be correlated with bank size. Also, large banks make more loans than smaller banks. So the coefficient on scoring could be picking up the effect of bank size rather than whether or not the bank uses credit scoring. This is just an example; other bank-specific variables might have a similar effect.

Similarly, the authors should consider including more variables to control for differences in loan demand across tracts. They do make a point in saying that it makes a difference whether firm revenues are included or not.

Despite the possibilities for revising the paper, I think this paper is a good first look at trying to understand whether lenders that use credit scoring behave differently from banks that do not use scoring. The aspect studied here is the volume of small-business lending they do, but one could extend the work in a number of interesting ways. For example, as the authors point out, small businesses are beginning to rely less on traditional bank loans for their funding. Indeed, in the Third Federal Reserve District, American Express is one of the largest providers of small-business loans, especially those with face values under $100,000. So the authors should consider extending their analysis to nonbank providers. The authors might also investigate what *types* of credit scoring models are being used by the respondents to their survey, and whether the characteristics of the scoring model and the way it is used affect the results. I'm not sure whether they have this information, but we know there are several generic models on the market, and some banks have their own proprietary systems. It would be interesting to know more details on the models being used, what cutoff levels the banks use for approving credit, and how the banks handle applications that don't make the cut.

If we accept as fact that credit scorers lend more than nonscorers, then the next question is, are they doing this by lending to higher-risk applicants, or are they able to find more applicants of the same risk to whom to extend loans? Some banks report they've been able to extend more loans under credit scoring than under their judgmental credit approval systems without increasing their default rates; it would be interesting to know if this is generally the case. Said differently, we'd like to know the long-term performance of these loans. Given the authors' data set, they should be able to make some headway along this dimension. They should have information on when the banks began using credit scoring for their small-business loans, and they have call report data on the banks. Thus, they should be able to say something about the performance of the credit scoring banks vs. the nonscorers. In fact, in this paper, it would have been nice to have some information about the characteristics of the scorers vs. the nonscorers.

Also, the paper looks at one particular way in which the lending behavior of banks that use scoring might differ from those that do not, namely, the volume of lending the banks do in low-mod areas. One could extend this to other aspects of the lending, e.g., the loan terms. Note that banks might be able to increase the volume of lending they do to the extent that credit scoring allows the bank to more accurately price risk.

This argument is an essential one underlying the Acs article. So let's turn to that article now. The Acs (1999) paper discusses some of the benefits of securitization and argues that credit scoring might encourage lending to small businesses by making securitization of these loans more feasible. As explained in the paper, securitization involves pooling together a group of loans and then using the cash flows of the loan pool to back publicly traded securities; the loans in the pool serve as collateral for the securities. The loan pool typically has more predictable cash flows than any individual loan, since the failure of one borrower to make a payment can be offset by another borrower who does make a payment. The expected cash flows from the loan pool determine the prices of the securities.

A crucial aspect of securitization is being able to accurately predict the cash flows of the loan pool so that the securities can be adequately priced. Credit scoring can help on this score by giving an estimate of default risk for each loan and by making small-business loans more homogeneous in terms of loan terms, collateral, and underwriting standards, which also makes default risk more predictable. Note that securitization could increase the amount of small-business lending, allowing nonbank lenders to play a larger role. The market would become more liquid; thus, diversification would be easier to achieve. Since diversification lowers risk, loan rates could be lower.

The limitations of credit scoring models, however, should be recognized. Acs (1999) makes three recommendations: (1) increase the number of banks using credit scoring; (2) demonstrate that credit scoring helps predict firm failure; and (3) demonstrate that a secondary market for small-business loans is needed. I'm not sure I'd buy into these recommendations until more research is done. At the very least, I would reorder them. First, we should determine whether a secondary market is needed, next, see if credit scoring works, and, if it works, then encourage banks to use it.

Both the Acs (1999) paper and the Padhi, et al. (1999) paper focus on how credit scoring will affect the volume of small-business lending. But neither paper explores how credit scoring might affect the *type* of small-business lending being done. Credit scoring may likely lead to increased competition among providers of small-business loans, especially those with face values under $100,000. It enables non-bank lenders that don't necessarily have a presence in the community to make a credit-scored loan. Scoring also increases the possibility that small-business loans can be securitized.

All of this might increase the amount of lending to small-businesses, but it will be a different kind of lending than we have traditionally seen. As some of the conference's papers argued, the traditional small-business loan is based on a relationship between the lender and borrower. The paper by Cole, Goldberg, and White (1998) shows that large and small banks do differ in the way they handle applications from small businesses. Large banks rely more on easily verified, interpreted, and quantifiable financial data, while smaller banks use more subjective criteria. The credit-scored loan is more like a credit card loan; it is a transactions-based loan rather than a relationship-based loan.

This difference between credit-scored and traditional loans is important. The typical bank-borrower relationship, which is built up over years of lending, allows for substantial flexibility in loan terms. A long-term relationship allows the bank to offer concessionary rates to a borrower facing temporary credit problems, which the bank can later make up for when the firm returns to health. Credit-scored loans are likely to have less flexible terms, with the terms set to maximize a lender's profits period-by-period rather than over the life of a relationship. Monitoring these borrowers would likely be more expensive for the lender, since many will come from outside the lenders' traditional lending markets.

But credit scoring, per se, has not caused this shift away from relationship lending toward transactions-type lending. Given the other changes taking place in financial markets, this shift toward commoditization of small-business loans and away from relationship loans would have occurred even without credit scoring.

Research by Berlin and Mester (1999) shows that an important part of a relationship loan is the ability of a bank to smooth interest rates over a business cycle. But we find that as new competitors (like mutual funds) have come into the funds market, and banks lose their ability to attract core deposits (the rates of which are relatively insensitive to the market), banks have also lost the ability to offer the kind of insurance afforded by smoothing loan rates. Hence, relationship loans have lost some of their attractiveness, and banks have lost some of their market share to other nontraditional lenders. Also, Berlin and Mester (1998) found evidence that relationship lending has become less profitable in recent times. So lost power on the deposit side of the market has affected the lending side. This would have happened regardless of whether credit scoring was invented.

Also, industry consolidation has contributed to the shift. Research by Mester, Nakamura, and Renault (1998) shows that the information a bank gets by seeing everyday credit flows into a firm's checking account is very helpful to the bank in monitoring the firm's loans. But as banks have gotten larger, and have expanded interstate, they are more often lending to nonlocal borrowers for whom they do not have this type of information. This means their ability to offer relationship loans is lessened.

The other interesting thing about consolidation is that we typically say that technological change has contributed to industry consolidation, and that is probably true. For example, the costs of setting up an automated loan processing system are not insubstantial. The more loans a bank makes, the more it can spread these fixed costs. Thus, the technology requires a larger minimum efficient scale. But it is also true, at least in the case of credit scoring, that consolidation will spur the technology. Remember that to build a better scoring model, you need a lot of loan application data. Only the largest banks had this information before Fair, Isaac and RMA put together data from a consortium of banks. With consolidation taking place in the industry, we might expect the scoring models to become more accurate.

So I see an equilibrium with two types of small-business loans. A small business whose financial documentation is easier to evaluate, that is more insulated from economic downturns or temporary problems, and that therefore, doesn't place high value on the flexibility of a relationship loan, will opt for a credit-scored loan offered by larger banks and nonbanks. These are the types of loans that are likely to be able to be securitized. On the other hand, businesses that find it hard to qualify for loans based solely on their credit scores, but that, nevertheless, are creditworthy on closer inspection or whose financial condition is harder to evaluate, will need to seek funding from the relationship lenders and will value the more flexible credit terms afforded by a relationship loan. They should expect to pay something for this flexibility. Smaller banks will maintain their advantage over larger banks in monitoring loans, since they have a good knowledge of the local markets in which they and their borrowers operate. So small banks will retain their niche in relationship lending, although it is likely to be a smaller niche.

Businesses that have turned to transactions-based loans have not really experienced life in an economic downturn with one of these loans. It could easily be that firms have to live through a downturn before they are able to place a value on having a relationship loan. Banks are also going to have to live through a downturn before they know how accurate their models are. This means the transition to the new equilibrium might not be smooth and painless.

If this is true, it raises an interesting question about the effect of shocks on the macroeconomy. Will the shift away from relationship loans lead to an economy in which macroeconomic shocks have larger effects? What happens if we move from a world in which a majority of lenders are able to insulate their small-business borrowers from economic shocks, to one in which the majority of lenders no longer play that role? What happens if all lenders use basically the same credit scoring model in their loan approval process? Any one lender might not find it desirable to remain a relationship lender, but the economy might be better off if some institutions did.

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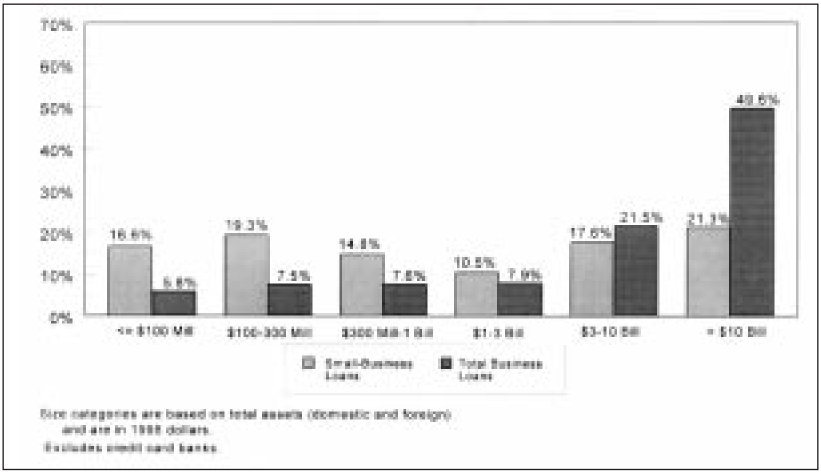
FIGURE 1

Distribution of Small-Business Loans and Total Business Loans, By Bank Size

Banks in the U.S., 1994



Distribution of Small-Business Loans and Total Business Loans, By Bank Size

Banks in the U.S., 1998

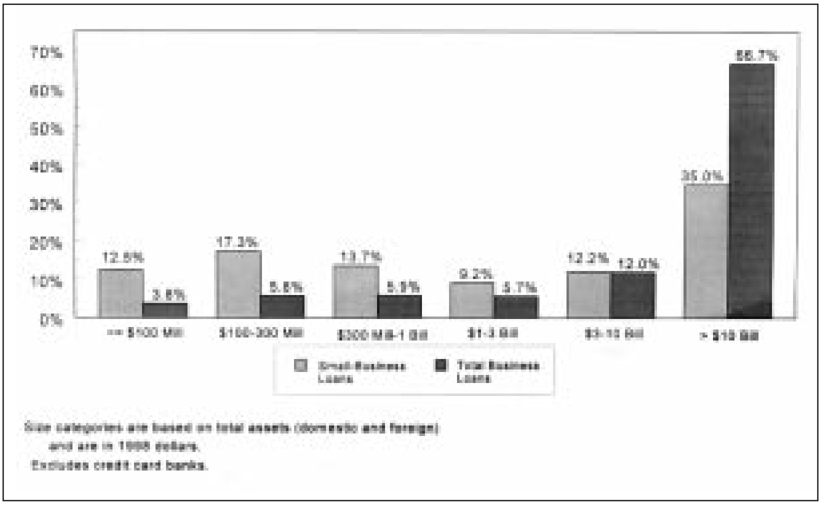
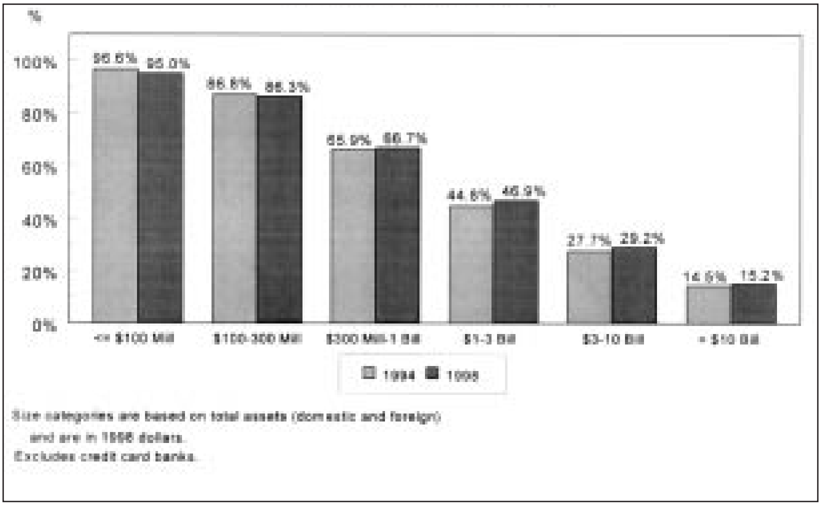


FIGURE 2

Ratio of Small-Business Loans to Total Business Loans, By Bank Size

Banks in the U.S., 1994 vs. 1998



References

Acs, Zoltan. "Development and Expansion of Secondary Markets for Small Business Loans," this volume.

Avery, Robert B., Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner. "Credit Risk, Credit Scoring and the Performance of Home Mortgages," *Federal Reserve Bulletin*, 82, July 1996, pp. 621-648.

Berlin, Mitchell, and Loretta J. Mester. "On the Profitability and Cost of Relationship Lending," *Journal of Banking and Finance*, 22, August 1998, pp. 873-897.

_______. "Deposits and Relationship Lending," with Mitchell Berlin, *Review of Financial Studies*, 12, Fall 1999, forthcoming.

Cole, Rebel A., Lawrence G. Goldberg, and Lawrence J. White. "Cookie-Cutter versus Character: The Micro Structure of Small Business Lending by Large and Small Banks," Working Paper FIN-98-022, Department of Finance, New York University, 1998.

Mester, Loretta J. "What's the Point of Credit Scoring?," *Business Review*, Federal Reserve Bank of Philadelphia, September / October 1997, pp. 3-16.

Mester, Loretta J., Leonard I. Nakamura, and Micheline Renault. "Checking Accounts and Bank Monitoring," Working Paper No. 98-24, Federal Reserve Bank of Philadelphia, December 1998.

Padhi, Michael S., Lynn W. Woosley, and Aruna Srinivasan. "Credit Scoring and Small Business Lending in Low- and Moderate-Income Communities," this volume.