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The Effect of Credit Scoring on Small Business Lending in Low- and Moderate-Income Areas

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Abstract: This paper empirically examines the effect of the use of credit scoring by large banking organizations on small business lending in low- and moderate-income (LMI) areas. Using census tract level data for the southeastern United States, the authors estimate that credit scoring increases small business lending by $16.4 million per LMI area served. Furthermore, this effect is almost 2.5 times larger than that estimated for higher income census tracts ($6.8 million). The authors also find that credit scoring increases the probability that a large banking organization will make small business loans in a given census tract. The change in this probability is 3.8 percent for LMI areas and 1.7 percent for higher income areas. These findings suggest that credit scoring reduces asymmetric information problems for borrowers and lenders and that this is particularly important for LMI areas, which lenders may have historically bypassed because of their questionable economic health.

JEL classification: G2, O1, O3, E5

Key words: credit scoring, small business lending, low-income, Community Reinvestment Act

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I. Introduction

Over the past decade, advances in information technology have transformed our society. Indeed, macroeconomists have marveled at the increases in productivity and wealth creation coupled with an absence of significant inflationary pressures, while microeconomists have noted the attendant consumer benefits derived from many lower priced products and services. Nevertheless, there has been little discussion of how the benefits of this improved technology are distributed along demographic lines, such as income.

This paper provides empirical evidence on whether households and firms operating in low- and moderate-income (LMI) areas have benefited from the adoption of a single new technology: credit-underwriting software (i.e., credit scoring) designed to evaluate small business loan applications. Credit scoring models have revolutionized lending by directly feeding credit reporting agency data into statistical models that predict the probability of borrower default. Consequently, under this approach, loans are processed quicker and loan officers play a diminished role in the decision-making process.

Specifically, we examine the net effect of the use of small business credit scoring models by large banking organizations in funding firms located in LMI areas. Furthermore, we compare this effect to that experienced by middle- and high-income (MHI) areas in order to discern its relative magnitude. This study is important not only because it examines whether LMI areas benefit from the adoption of new technologies, but also because it focuses on the provision of credit – one of the primary components of any policy proposal for creating economic opportunity in traditionally under-served areas.

The rest of our paper is organized in the following manner. Sections II presents background information on small business credit markets and credit scoring with a particular focus on LMI areas. Section III discusses the four types of data used in this study. Section IV outlines our hypothesis tests and provides sample statistics. Regression results and conclusions are presented in Sections V and VI, respectively.

II. Small Business Lending, Credit Scoring, and LMI Areas

Theories concerning small business credit markets emphasize the existence of significant information asymmetries between borrowers and lenders (Nakamura, 1993). It is also believed that such market imperfections can result in credit rationing by lenders, particularly when loans are unsecured (Stiglitz and Weiss, 1981). To mitigate such problems, borrowers and lenders have historically used long-term relationships, or close and continuous interactions that generate useful information about the borrowers' financial states (Frame, 1994). Moreover, small businesses are thought to be dependent on local banks for such relationship-based borrowing. Empirical evidence confirms both the value of lending relationships (Petersen and Rajan, 1994; Berger and Udell, 1995; and Cole, 1998) as well as the use of local commercial banks for small business credits (Elliehausen and Wolken, 1990).

In the wake of unprecedented consolidation of the U.S. commercial banking industry during the 1990's, many policymakers have expressed concern that the emerging institutions may significantly reduce the availability of credit to small firms. This conjecture is based primarily on the fact that bank call report data indicate that small banks hold a greater percentage of their assets in small business loans than do large banks (Berger, Kashyap, and Scalise, 1995).

Indeed, Berger and Udell (1996) synthesize two theories positing that the provision of banking services to small businesses decreases with bank size and organizational complexity. The first is that the small business lending is fundamentally different from large firm lending in that the former credits are more information intensive and relationship-driven. The second, based on the work of Williamson (1967), emphasizes managerial diseconomies of scale with the provision of multiple activities in large, complex organizations.[1] Berger and Udell's empirical tests indicate that large banks tend to charge relatively lower loan rates to and less often require collateral of small business borrowers. However, they find that large banks reduce their volume of relatively costly relationship loans via price or quantity rationing. Related work by Cole, Goldberg, and White (1998) indicates that large banks typically employ standard financial statement criteria in the loan decision process, while small banks focus more on their impression of borrower character.

The aforementioned research suggests that small business loan underwriting is conducted differently in large and small banks. Today, in fact, most large banks use automated underwriting systems for small business lending based upon credit scores. Credit scoring is the process of assigning a single quantitative measure, or score, to a potential borrower representing an estimate of the borrower's future loan performance (Feldman, 1997). While credit scores have been used for some time in the underwriting of consumer loans, this technology has only recently been routinely applied to commercial credits. This is because commercial loans were thought to be too heterogeneous and that documentation was not standardized either within or across institutions (Rutherford 1994/1995). However, credit analysts ultimately determined that

[1] For example, the trend toward large banking organizations with expanded product lines and increased geographic dispersion may complicate the managerial structure of the banking organization. This can result in increased layers of management (vertical complexity) and an increased number of parallel functions (horizontal complexity.)

the personal credit history of small business owners is highly predictive of the loan repayment prospects of the business, especially for loans under $100,000.[2] Thus, personal information is obtained from a credit bureau and then augmented with basic business-specific data to predict repayment. Eisenbeis (1996) presents an excellent overview of the history and application of credit scoring techniques to small business loan portfolios.

According to Feldman (1997), credit scoring will alter small business lending in three areas: (1) the interaction between borrowers and lenders; (2) loan pricing; and (3) credit availability. First, credit scoring allows lenders to underwrite and monitor loans without actually meeting the borrower. This development is in stark contrast to the perceived importance of a local bank-borrower relationship. In fact, because of scoring systems, borrowers can obtain unsecured credit from distant lenders through direct marketing channels. Second, the price of small business loans should decline -- especially for high credit quality borrowers that will no longer will have to bear the cost of extensive underwriting. Also, increased competition -- resulting from small businesses having access to more lenders -- should further lower borrowing costs. Third, credit scoring should increase credit availability for small businesses. Better information about the repayment prospects of a small business applicant makes it more likely that a lender will price the loan based on expected risk, rather than denying the loan out of fear of charging too little. Moreover, the widespread use of credit scoring should increase future prospects for asset securitization by encouraging consistent underwriting standards.

Empirical evidence concerning Feldman's predictions is limited to the effect of credit scoring on small business credit availability. Indeed, Frame, Srinivasan, and Woosley (2001)

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

estimate that the use of credit scoring increases the portfolio share of small business loans by 8.4 percent for their sample of large commercial banking organizations. Of course, in light of the findings of Berger and Udell (1996) and Cole, et. al. (1998), this increase in lending likely represents a combination of new business offset somewhat by a decline in relationship-based loans by large banks.

While the principles outlined above apply uniformly to small business credit markets, those geographic areas characterized by a large concentration of LMI households may be affected in additional ways. First, due to asymmetric information problems, banks may have historically elected to more readily ration small business credit in LMI areas due to their questionable economic health. That is, lenders may have "redlined," or used the physical location of the business as a crude proxy for the riskiness of the loan. Credit scoring, by reducing these informational asymmetries, should serve to reduce redlining and further increase the flow of small business loans in LMI areas. Second, credit scores are designed to be objective risk measures that may significantly reduce the willingness and ability of a loan officer to discriminate based upon the borrower's race.[3] This is particularly important in LMI areas in which minority groups are generally over-represented. Thus, we expect increased objectivity to increase credit availability in LMI areas. Third, credit scoring models may not accurately measure the probability of loan repayment for LMI borrowers if the population of loans used to build the model was not sufficiently diverse. This could either help or hinder small business credit availability in LMI areas depending upon whether the model parameters are valid for the LMI sub-population.

[3] Ladd (1998) reviews both the theoretical motives and empirical evidence of racial discrimination in lending.

III. Data

To examine the effect of credit scoring on small business lending in LMI areas, we focus on the lending patterns of a sample of large banking organizations in each census tract in the southeastern United States (Southeast). We define the Southeast as those states located in the Sixth Federal Reserve district: Alabama, Florida, Georgia, Louisiana, Mississippi, and Tennessee. We limit our analysis in this way for two reasons. First, we examine large banking organizations because they are much more likely to use credit scoring for small business lending than smaller institutions. This is due to the high start-up costs both in terms of purchasing software and training personnel to operate the system. Second, we employ regional analysis exclusively for computational convenience. We have no reason to believe that our results could not be generalized nationwide.

Overall, we use four different types of data in our analysis: (1) demographic data for each census tract; (2) business information for each census tract; (3) bank data at both the census tract and institutional levels; and (4) survey data on the use of credit scoring by large banking organizations. We then combine these data to uncover the determinants of small business lending activity by large banking organizations in each census tract in the Southeast.

First, using the Census Bureau's LandView III software, we collected the median household income and the racial characteristics for each census tract in the Southeast. We examined median household income for each census tract relative to either its Metropolitan Statistical Area (MSA) for urban census tracts or total non-metropolitan area of its state for rural census tracts. That is, each census tract is denoted as either "low-income," "moderate-income," "middle-income," or "high income" based on its median income as a percent of broader area

(MSA or state) median income.[4] The latter data were obtained from SNL Securities' SNL DataSource. Table 1 presents the number and percent of rural and urban census tracts assigned to the income classifications for southeastern census tracts.

[Table 1 about here.]

Second, we collected information on the total number of businesses in each census tract sorted by total annual revenues from Dun and Bradstreet. We then estimated total small business revenues in each census tract as the sum of the product of the number of businesses in each revenue category multiplied by the median revenue specified by each category.[5] Unfortunately, because the Dun and Bradstreet data do not cover all census tracts, we had to drop 83 from our analysis (1.1 percent).[6]

Third, we used several sources to extract data for our sample of 99 large banking organizations. Data on the total dollar value of small business loans originated in 1997 in each census tract in the Southeast, by bank, are collected from the CRA small business lending database. This database, prepared by the Federal Reserve Board of Governors, provides total commercial loan originations of less than $1 million, by reporting institution, for each census

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[4] Following Bostic and Canner (1998), we define "low-income" communities as ones with median household income less than 50 percent of their larger areas'. "Moderate-income" means that median household income that is at least 50 percent but less than 80 percent of the broader area. "Middle-income" denotes median household income is between 80 percent and 120 percent of the area's median household income. "High income" means median household income is greater than 120 percent of the area's median household income.

[5] For example, consider a census tract where there are two businesses with revenues less than $50,000, two with revenues between $50,000 and $100,000, and one business with revenues between $100,000 and $250,000. We estimate total small business revenue to be $375,000 = (2 * $25,000) + (2 * $75,000) + (1 * $175,000) .

[6] Of these, 23 were low- or moderate-income and 60 were middle- or high-income. Further, 22 were urban census tracts and 61 were rural.

tract in the United States.[7, 8] For reasons discussed below, we confine our analysis to those loans with original amounts less than $100,000. We also collected aggregate information for each banking organization, such as total assets, total equity, and total small loans to businesses from the bank call reports. The FDIC's Summary of Deposits data provided information on specific bank branch locations.

Lastly, we use data from a telephone survey of the 200 largest U.S. banking organizations (as measured by total domestic banking assets as of June 30, 1997).[9] The Federal Reserve Bank of Atlanta conducted this survey of small business credit scoring in January 1998. Some 99 institutions responded to the telephone survey, of which 61 reported credit scoring small business loans under $100,000 for most of 1997. Frame, Srinivasan, and Woosley (2001) provide a complete discussion of the small business credit scoring survey and responses.

The large banking organizations examined in this study are exclusively those that responded to the Federal Reserve Bank of Atlanta's telephone survey. Each of these institutions report small business lending information under the CRA. Indeed, 77 of the respondents (77.8 percent) had originated small business loans in the Southeast in 1997. This figure includes 50 institutions that reported using credit scoring (82.0 percent of scorers) and 27 that did not (71.1 percent of non-scorers).

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[7] The data are filed with the Federal Reserve Board of Governors regardless of a reporting bank's primary regulator. This information is required under an interagency revision of Community Reinvestment Act regulations by the federal bank and thrift regulators in 1995. Individual bank disclosures and aggregated data are publicly available at www.ffiec.gov/cra.

[8] Technically, this data represents "small loans to businesses," rather than small business loans. Nevertheless, as noted by Bostic and Canner (1998), because small businesses are more likely than larger ones to borrow small amounts, the CRA data (like the similar Call Report data) on small loans are likely to provide a reasonable measure of the extension of credit to small businesses. See Bostic and Canner (1998) for a complete discussion of the CRA small business lending database – including some potential limitations for conducting policy research and analysis.

IV. Hypothesis Testing

Based on the discussion in Section II, we believe that credit scoring will have an overall positive effect on small business credit availability in LMI areas and that this effect may be larger than that for MHI areas. This would primarily result from lenders facing lower fixed underwriting costs, reducing their use of proxies (e.g., borrower location) for individual creditworthiness, and having increased objectivity. However, credit scoring models may also effect credit availability (either positively or negatively) if the data used to estimate them is not representative of LMI borrowers. Moreover, credit scoring may result in the rationing of some "relationship-based" loans away from large banks. Unfortunately, our analysis cannot distinguish among these individual effects, but rather captures the *net* effect.

The dependent variable in our empirical model is the total dollar volume of small business loans under $100,000 in each census tract (SBL) in the Southeast for each banking organization that responded to our telephone survey. SBL is scaled by $1 million. We then model SBL as a function of whether the banking organization uses credit scoring (SCORE) as well as several other variables accounting for variation between banking organizations and census tracts. We now discuss each independent variable, in turn, according to its predicted effect on the supply of or demand for small business loans.

We include three variables in our empirical model designed to capture each banking organization's propensity to supply a certain level of small business credit. Each of these variables was constructed from bank Call Report data aggregated to the bank holding company level. First, we include institution size as defined as the natural logarithm of total domestic banking assets (LNASSETS). This variable is included to capture the fact that larger banking

[9] The sample was further limited to exclude credit card banks and institutions with less than 0.50 percent of their total assets in small business loans. These exclusions reduced the sample size to 190.

organizations will tend to underwrite more loans in any single census tract, but that this effect diminishes as size increases due to demand constraints. Second, we include the banking organization's overall ratio of small business loans to total domestic banking assets (SBLRATIO). This variable is included to account for variation between institutions in their propensity to make small business loans. That is, some banks may have more of an "institutional focus" on small business lending than others. Third, we include the banking organization's overall leverage ratio as defined as the ratio of total equity to total assets (LEVERAGE). We expect this variable to be positively related to the volume of small business loans because of the risks associated with this type of lending.

Our empirical model also includes several variables that may affect the demand for small business credit in each census tract. First, we include a dummy variable (RURAL) that takes a value of one for rural census tracts. To the extent that present and future investment opportunities are lower in rural areas, we expect this variable to be negative. Second, we include median household income (HHINCOME). Because small business credit scoring models rely so heavily on the financial position of the principal, we expect this to be positively related to the level of lending. Lastly, we include total small business revenues in each census tract (SMALLBUSREV), with small businesses defined as all firms with total revenues below $1 million. We expect the equilibrium level of small business lending to be positively related to SMALLBUSREV, as greater business revenue may represent increased capacity to take on debt.

We also include three variables indicating the racial characteristics of the census tracts: the percent of individuals identified as Hispanic (HISPANIC), the percent of individuals identified as Asian (ASIAN), and the percent of individuals identified as black (BLACK). These variables may have either demand-side or supply-side interpretations. A supply-side relationship between these race variables and small business lending (after controlling for other relevant factors) could be interpreted as discrimination in the form of geographic “redlining” (if the effect is negative) or policy intervention through effective enforcement of the Community Reinvestment Act (if the effect is positive). On the demand side, one might conjecture that, as a cultural matter, some minority groups are less comfortable seeking bank credit. This would be indicated by a negative relationship between any of the race variables and SBL.

Two binary variables related to the geographic location of the bank may also have demand-side or supply-side interpretations. The first is whether the banking organization has a bank branch located in the census tract (TRACTBRANCH). The second indicates whether the banking organization has a bank branch located in the relevant geographic banking market (county or MSA depending on whether the census tract is located in a rural or urban area), but outside the census tract (MKTBRANCH). While we expect a positive relationship between these variables and the volume of small business loans in the census tract, this finding may stem from either the customer’s geographic convenience (demand-side) or better knowledge or comfort level with lending in the local area by the bank (supply-side).

Tables 2 and 3 provide the sample statistics for all LMI and MHI census tracts in the Southeast, respectively. Sample statistics on the banking organization-specific variables, SCORE, LNASSETS, SBLRATIO, and LEVERAGE are identical for our two samples. As mentioned earlier, 61 of the 99 (62 percent) institutions responding to the telephone survey used credit scoring for small business loans for most of 1997. Also, on average, the 99 large banking organizations committed 2.4 percent of their portfolios to small business loans and had an average leverage ratio of 8.4 percent.

By examining the census-tract specific information, we can detect the important differences between the LMI and MHI samples. For the 99 large banking organizations, we find that the average amount of small business lending in LMI areas in 1997 was $2.8 million, compared with $3.6 million in MHI areas. The large banking organizations also, on average, have roughly the same branch presence in LMI census tracts as in MHI areas. Turning to the demographic information, we find that rural census tracts comprise about 22 percent of our LMI sample and 32 percent of our MHI sample. Average small business revenues were slightly higher in MHI census tracts ($75.5 million) than LMI census tracts ($69.8 million). The racial characteristics of the LMI and MHI areas were similar, on average, for both Hispanics (4.3 percent and 3.7 percent, respectively) and Asians (0.7 percent and 0.9 percent, respectively). However, the average percent of black residents in LMI areas was 50.3 percent versus 14.1 percent in MHI areas.

[Insert Tables 2 and 3 about here.]

Ultimately, we specify the following cross-sectional relationship between small business lending in each census tracts and the demographic and bank characteristics described above:

(1) SBL = *f*(SCORE, LNASSETS, SBLRATIO, LEVERAGE, RURAL, HHINCOME, SMALLBUSREV, HISPANIC, ASIAN, BLACK, TRACTBRANCH, MKTBRANCH)

Because most of the large banking organizations in our sample do not report small business loans in every census tract under study, the dependent variable in equation (1) is often coded with zero. Due to this censoring, we estimate the statistical model using the Tobit procedure. This is done for both the LMI and MHI groups. The regression results are discussed in the next section.

V. Regression Results

Table 4 provides the Tobit estimates for our censored regression of census-tract-level small business lending for both the LMI and MHI sub-groups. In both cases, we find that credit scoring is associated with increased small business lending activity by large banking organizations. Similarly, banking organization size, net worth, institutional focus on the small business lending segment, and local branches were also positively related to the level of small business lending in both LMI and MHI areas. Rural areas and those with higher small business revenues also had more small business lending. Census tracts with a greater proportion of black residents were associated with lower levels of small business lending by large banking organizations in both LMI and MHI areas. Small business credit availability is positively related to household income only in MHI areas, but statistically unrelated in LMI areas. This may reflect the fact that there is much greater household income variation in the LMI sample versus the MHI sample.[10]

While the parameter estimates presented in Table 4 are useful for discussions of statistical significance, the data censoring hinders economic interpretations and comparisons across samples. Thus, we calculate "marginal effects" for each independent variable evaluated at their respective sample means (Greene 1997). Specifically, we use a decomposition developed by McDonald and Moffitt (1980) to uncover the predicted change in small business lending in census tracts due to credit scoring, conditional on a large banking organization making loans there. This decomposition also allows us to estimate the change in the probability of lending in a particular census tract stemming from the use of credit scoring. Formally, McDonald and Moffitt's decomposition can be expressed as:

(2) $\partial Ey / \partial Xi = F(z) [\partial Ey^* / \partial Xi] + Ey^* [\partial F(z) / \partial Xi]$,

where Ey is the expected value of the unobserved (latent) dependent variable, Ey* is the expected value of the observed dependent variable, X is a matrix of $i=1,...,N$ independent variables, and F(z) is the cumulative normal distribution function for a standardized random variable, $z = X\beta / \sigma$. As noted by McDonald and Moffitt (1980), the total change in the dependent variable arising from a change in the independent variables, $\partial Ey / \partial Xi$, can be disaggregated into two parts. The first is the change in y of those observations above the limit (i.e., uncensored), weighted by the probability of being above the limit. The second is the change in the probability of being above the limit (e.g., zero), weighted by the expected value of y if above the limit. We focus our attention on two terms: (1) $\partial Ey^* / \partial Xi$, or the average change in the dependent variable given a change in the independent variables and that $y>0$; and (2) $\partial F(z) / \partial Xi$, or the change in the probability of observing $y>0$ given a change in the independent variables.

Tables 5 and 6 present the total estimated marginal effects ($\partial Ey / \partial Xi$) and decomposition for the Tobit estimates of equation (1). To begin, we estimate that credit scoring increases small business lending by \$16.4 million in LMI census tracts and \$6.8 million in MHI tracts for our sample of large banking organizations operating in the Southeast. Credit scoring also increases the probability of large banking organizations making small business loans in these census tracts

[10] . This is reflected by the standard deviations of HHINCOME reported in Tables 2 and 3.

by 3.8 percent and 1.7 percent, respectively. These findings are consistent with reduced credit rationing in LMI areas due to significantly improved information about borrower creditworthiness. As a result, banks are likely becoming much less inclined to use geographic location or neighborhood racial characteristics as a proxy for borrower creditworthiness. Overall, this demonstrates considerable benefits to LMI areas from a technological improvement that is important to future economic development.

Examining the banking organization variables, the marginal effects for LNASSETS and SBLRATIO are roughly the same across samples. However, higher capitalization appears to be more important for lending in LMI areas – perhaps due to risk considerations. The presence of branches in either the census tract or banking market (outside of the census tract) are strongly positively related to small business lending for both the LMI and MHI samples. For the LMI sample, census tract branches ($360 million) appear to be more economically important than branches otherwise located within the banking market ($292 million). Moreover, the effect of branching seems to have a marginally greater impact in LMI areas. These results reflect the strong local connections between the banks and their borrowers.

With respect to the census tract variables, we find that rural census tracts and those with greater small business revenues receive larger credit volumes. For example, we estimate that rural areas within the LMI sample receive an extra $43.4 million in small business credit than their urban counterparts. This estimate is $29.3 million for MHI areas. The effect of ethnicity on small business lending appears generally to be small. For LMI and MHI census tracts, the proportion of Hispanic and Asian residents has no statistical relationship (at the 90 percent level) with the volume of small business lending in a community. Also, while the proportion of black residents is negative and statistically related to small business lending for both LMI and MHI census tracts, the effect of this proportion (consistent across samples at about 0.19) is economically unimportant. It means that for every unit increase in the percent black of a census tract's population, small business lending is about $1,900 lower. Furthermore, none of the race variables had a material influence on the probability of large banking organizations making small business loans in either LMI or MHI census tracts.

VI. Conclusions

This paper empirically examined the effect of credit scoring on small business lending in low- and moderate-income (LMI) areas. Specifically, our analysis focused on lending activity of 99 large banking organizations in the southeastern United States as of year-end 1997. Overall, we estimate that credit scoring increases small business lending in LMI census tracts by $16.4 million per institution per census tract in which they underwrite loans. This effect is about 2.5 times larger than that estimated for higher income census tracts. The use of credit scoring also increases the probability that a large banking organization will make loans in a census tract. For LMI areas, the probability increases by 3.8 percent and for MHI areas 1.7 percent.

Relationships between our other variables of interest and small business lending were fairly consistent for LMI and MHI census tracts. First, for the large banking organizations, their size, institutional focus on small business lending, capitalization, and local branching were all positively related to small business lending in all areas. Second, for census tract demographics, rural areas and those with greater small business revenues attract more capital. Third, the effect of ethnicity on small business lending is very small. Indeed, while census tracts with larger proportions of black residents have statistically smaller levels of small business lending, the amount ($1,900) is economically unimportant.

Our analysis suggests that credit scoring is increasing small business lending by reducing asymmetric information problems between borrowers and lenders. This effect appears to be particularly pronounced and important for LMI areas, which historically have had difficulty attracting capital. Overall, these results suggest that low-income areas do benefit from technological enhancements – and that sometimes these benefits are greater than those experienced in higher income areas.

Table 1
Number of Rural and Urban Census Tracts in the Southeastern United States
(Sorted by Median Household Income Classification)

	Rural (Number)	Rural (Percent)	Urban (Number)	Urban (Percent)	Total (Number)	Total (Percent)
Low Income	46	7.42	574	92.58	620	100.00
Moderate Income	441	28.20	1123	71.80	1564	100.00
MiddleIncome	1406	38.11	2283	61.89	3689	100.00
High Income	399	22.18	1400	77.82	1799	100.00
Total	2292	29.87	5380	70.13	7672	100.00

Table 2
Summary Statistics
Low- and Moderate Income Census Tracts

	Mean	Standard Deviation	Minimum	Maximum
SBL	2.7510	56.5132	0.0000	18,452.00
SCORE	0.6163	0.4863	0.000	1.0000
LNASSETS	16.3007	1.3238	14.1778	19.6792
SBLRATIO	0.0240	0.0183	0.0019	0.1055
LEVERAGE	0.0844	0.0169	0.0535	0.1510
RURAL	0.2193	0.4137	0.0000	1.0000
HHINCOME	15,167.97	4,951.21	4,999.00	28,726.00
SMALLBUSREV	69.8154	96.1807	0.0250	1,590.23
HISPANIC	0.0425	0.1261	0.0000	0.9620
ASIAN	0.0074	0.0219	0.0000	0.4457
BLACK	0.5038	0.3453	0.0000	0.9994
TRACTBRANCH	0.0060	0.7691	0.0000	1.0000
MKTBRANCH	0.0599	0.2372	0.0000	1.0000

Table 3
Summary Statistics
Middle- and High-Income Census Tracts

	Mean	Standard Deviation	Minimum	Maximum
SBL	3.6337	56.9998	0.0000	14,168.00
SCORE	0.6164	0.4863	0.000	1.0000
LNASSETS	16.3011	1.3240	14.1778	19.6792
SBLRATIO	0.0240	0.0183	0.0019	0.1055
LEVERAGE	0.0844	0.0169	0.0535	0.1510
RURAL	0.3235	0.4678	0.0000	1.0000
HHINCOME	29,655.25	11,330.45	14,133.00	150,001.00
SMALLBUSREV	75.5140	138.5568	0.0250	6,536.13
HISPANIC	0.0371	0.0956	0.0000	0.9224
ASIAN	0.0085	0.0115	0.0000	0.2183
BLACK	0.1405	0.1841	0.0000	0.9986
TRACTBRANCH	0.0078	0.0882	0.0000	1.0000
MKTBRANCH	0.0542	0.4678	0.0000	1.0000

Table 4
Parameter Estimates for LMI and MHI Census Tracts
Estimation by Tobit

	LMI Census Tracts	MHI Census Tracts
Variable	Estimate	Estimate
Intercept	-3903.3000*	-3645.7000*
	(2067.8727)	(6580.7779)
SCORE	44.4820*	19.0601*
	(18.9829)	(12.7390)
LNASSETS	116.8680*	115.0003*
	(824.3787)	(2821.6194)
SBLRATIO	4737.7000*	4794.7000*
	(330.2672)	(1255.0102)
LEVERAGE	6577.3000*	5621.6000*
	(886.9330)	(2379.6586)
RURAL	117.4494*	78.5491*
	(120.9712)	(220.1783)
HHINCOME	-0.0007	0.0012*
	(0.5889)	(40.7100)
SMALLBUSREV	0.6546*	0.1867*
	(599.3920)	(700.3628)
HISPANIC	-43.0270	-29.2550
	(2.4516)	(2.2975)
ASIAN	-293.8640	198.7040
	(2.5047)	(1.2453)
BLACK	-53.6810*	-51.5050*
	(16.2511)	(18.0523)
TRACTBRANCH	985.2683*	909.3537*
	(2748.2255)	(9332.9916)
MKTBRANCH	762.2829*	693.4827*
	(4059.2873)	(12363.6149)

Chi-squared statistics in parentheses
* Indicates statistical significance at the 99 percent level.

Table 5
McDonald and Moffitt Decomposition of Marginal Effects for
Small Business Lending in LMI Areas
∂Ey / ∂Xi = F(z) [∂Ey* / ∂Xi] + Ey* [∂F(z) / ∂Xi]

	Marginal Effect	Decomposition			
Variable	∂Ey / ∂Xi	F(z)	[∂Ey* / ∂Xi]	Ey*	[∂F(z) / ∂Xi]
SCORE	22.8514	0.5236	16.4310	372.6045	0.0382
LNASSETS	115.2439	1.0000	115.2088	1878.4907	0.0000
SBLRATIO	2747.2013	0.5960	1934.6272	405.8400	3.9281
LEVERAGE	5825.8715	0.8884	4549.7385	650.9020	2.7404
RURAL	60.3257	0.5222	43.4007	372.0200	0.1012
HHINCOME	-0.0003	0.4906	-0.0003	358.7964	-0.0000
SMALLBUSREV	0.3504	0.5397	0.2504	379.6115	0.0006
HISPANIC	-0.1865	0.4986	-0.1356	362.0805	-0.0003
ASIAN	-1.5461	0.4980	-1.1248	361.8198	-0.0027
BLACK	-0.2564	0.4762	-0.1887	352.9739	-0.0005
TRACTBRANCH	496.0456	0.5050	359.6317	364.7307	0.8621
MKTBRANCH	408.0078	0.5394	291.6047	379.4752	0.6607

Table 6
McDonald and Moffitt Decomposition of Marginal Effects for
Small Business Lending in MHI Areas
∂Ey / ∂Xi = F(z) [∂Ey* / ∂Xi] + Ey* [∂F(z) / ∂Xi]

	Marginal Effect	Decomposition			
Variable	∂Ey / ∂Xi	F(z)	[∂Ey* / ∂Xi]	Ey*	[∂F(z) / ∂Xi]
SCORE	9.4031	0.5107	6.7991	342.4122	0.0173
LNASSETS	115.1619	1.0000	115.1512	1877.1036	0.0000
SBLRATIO	2897.0507	0.6064	2036.9253	383.3782	4.3347
LEVERAGE	4910.3456	0.8696	3763.2545	580.1228	2.8230
RURAL	40.8124	0.5237	29.3440	347.5876	0.0732
HHINCOME	0.0006	0.5317	0.0004	350.8230	0.0000
SMALLBUSREV	0.0948	0.5131	0.0685	343.3711	0.0002
HISPANIC	-0.1200	0.4992	-0.0872	337.9323	-0.0002
ASIAN	1.1309	0.5018	0.8212	338.9562	0.0021
BLACK	-0.2640	0.4929	-0.1926	335.5347	-0.0005
TRACTBRANCH	462.8727	0.5065	335.3350	340.7929	0.8598
MKTBRANCH	372.3795	0.5351	266.5579	352.1744	0.6524

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