# INTRAMETROPOLITAN PATTERNS OF SMALL-BUSINESS LENDING
## What Do the New Community Reinvestment Act Data Reveal?

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Discrimination and redlining in business lending have been cited as contributing to economic decline in lower-income neighborhoods. Until recently, bank regulators have not collected geographic data on business loans. Using new data collected by regulators, the author measures small-business lending flows to different types of neighborhoods in the Chicago metropolitan area. Although data limitations preclude a definitive finding of differential access to credit, lower-income and minority neighborhoods areas receive fewer loans after accounting for firm density, firm size, and industrial mix, findings that support the notion of geographic and/or race-based discrimination in marketing or approving loans.

**Problems of anemic or declining** business development in many low- or moderate-income neighborhoods continue to be of concern to policy makers and researchers (Bingham and Zhang 1997; Porter 1995; U.S. Department of Housing and Urban Development 1995). One potential contributor to such problems is inadequate access to credit by small businesses in these areas. Bates (1989) showed that levels of both financial equity and debt are important to the viability of start-up firms, with the latter being more important to minority-owned than white-owned firms. Some have argued that lending discrimination and geographic redlining have constrained access to credit by firms in lower-income areas and by black-owned businesses (Bates 1993; Dymski 1996).

Firms in low-income areas seeking loans might face either geographic discrimination, known as redlining, or individual-based discrimination against minorities or other protected groups. Moreover, discrimination may occur at various points of the borrowing process. Lenders might avoid marketing their

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products to geographic areas or to certain minority groups. They also might reject loan applications from firms in lower-income areas or from minority-owned businesses at rates higher than those from other firms with similar credit risks. Alternatively, lenders might approve smaller loans to discriminated firms, requiring more financial equity per dollar of debt, or charge interest rates that are higher than those offered to similar firms located elsewhere or owned by whites.

As a response to concerns over redlining, the 1977 federal Community Reinvestment Act (CRA) and its attendant regulations require banks and thrifts to offer small-business credit throughout their market areas and prohibit them from excluding low- and moderate-income sections of their larger market areas from their formal regulatory assessment areas (U.S. Department of the Treasury 1995).[1] This article examines new data made available under recent revisions to CRA regulations. These data, although not sufficient to confirm or deny racial or geographic discrimination in small-business lending markets, describe patterns of small-business lending across intrametropolitan space. They can be used to indicate whether bank lending flows are consistent with explanations of discrimination or redlining and whether the collection of more detailed loan data is warranted. Moreover, they can be used to model the general determinants of small-business lending flows, providing important information for economic development and bank regulatory policy.

## CRA REFORM IN THE 1990s

Until recently, bank examiners conducting CRA evaluations could analyze the geographic patterns only of residential mortgages because no geographic data on business loans were collected by regulators. In late 1993, the four federal bank regulatory agencies, led by the Treasury Department's Office of the Comptroller of the Currency, proposed for public comment a set of revised CRA regulations that contained major modifications in CRA evaluation procedures and in the lending data collected from banks. In addition to proposing that CRA evaluations be based more on outcomes, including lending activities, and less on bank process or reported efforts, the regulators proposed collecting and analyzing data on small-business loan applications similar to those collected for home mortgage applications under the 1989 revisions of the 1975 Home Mortgage Disclosure Act (HMDA), except that race and gender of firm owners would not be collected (Federal Financial Supervisory Agencies 1993).[2]

After receiving many comments, regulators revised their original proposal and reduced the reporting of small-business lending to reporting only on originations and not applications. At the same time, however, community groups persuaded the regulators to propose the collection of some data on the race of firm owners (Federal Financial Supervisory Agencies 1994). The small-business data reporting issues, especially the collection of racial information, were among the most controversial components of the CRA reform process. An existing Federal Reserve regulation (regulation B) actually prohibits even the voluntary collection of racial or ethnic data on business loans and would have been superseded by the revised proposal.

In 1995, the revisions to the CRA regulations were finalized (U.S. Department of the Treasury 1995). These final rules largely resemble the stripped-down data collection requirements of the 1994 revised proposal, except that the requirement for the collection of racial data was omitted. The final regulations require all but the smallest banks to report small-business lending volumes by census tract.[3] The data were collected for the first time in 1996, and the 1996 figures were disclosed in late 1997. Unfortunately, the aggregate nature of the data and the lack of detailed information on applications and denials, firm size, industry, credit history, and race prevent direct conclusions regarding geographic or race-based lending discrimination.[4] At the same time, these new data are important, and like studies of early HMDA data, their analysis will determine the extent to which lending varies by neighborhood income and race. Finally, studies of these data are likely to provide important evidence in ongoing debates over whether bank regulations will be changed to provide for the collection and disclosure of more complete and disaggregated data, such as those collected on mortgages.

## GEOGRAPHIC AND RACE-BASED CONSTRAINTS ON BUSINESS CREDIT

A number of factors might be expected to lead to an inadequate supply of credit to firms in lower-income neighborhoods. First, lenders might exhibit a form of pure discrimination, either geographic or individual-based, in which they choose to avoid making loans to firms in such areas or to minority-owned businesses because they have a taste for doing so. White loan officers, for example, might give preferential treatment to white firm owners, with whom they share a "cultural affinity" (Hunter and Walker 1995), or might prefer not to call on firms in low-income neighborhoods.

Second, lenders might discriminate statistically, using the race of the owner or neighborhood, or neighborhood income, as a signal of borrower risk or risk-adjusted profit. The lender might employ such signals in identifying potential loan applicants or in approving loan applications. If assessments of average risk among firms in a geographic area or minority group are biased high, a negative impact on credit access is clearly expected. However, even accurate assessments of average risk among a group of firms may result in statistical discrimination in which individual firms are assigned the average attributes of all firms in the geographic area or minority group. If average risk exceeds lenders' tolerance for risk, then entire groups or geographic areas may be denied credit access, even though some firms are creditworthy.

A third reason why lenders might underserve certain types of geographic or race-based groups of firms involves the notion of information externalities in lending. Lang and Nakamura (1993) provided a theory of redlining based on incomplete information. If lenders receive few applications from lower-income neighborhoods, they have little information about how to evaluate applications from these areas. Because of this incomplete information, lenders deny applications from these areas at higher rates than those from other higher-income areas. In this model, lending generates information, including data on property values and borrower risk, which is a public good that is beneficial to other lenders.

In this article, I identify the determinants of credit flow to small businesses with annual sales of less than $1 million. There are at least two reasons why these small firms may be most likely to suffer from differential credit access across urban space. First, Bates (1997) has shown that black-owned start-up firms are able to leverage their initial equity investments at lower rates than white-owned firms. That is, controlling for other firm characteristics, black start-ups receive smaller amounts of bank debt per dollar of owner equity than white-owned firms. Second, larger, more established firms are likely to be lower risk and generate higher profit margins for the bank. Because discrimination is expected to be most important at the margin, a lender's racial or geographic preferences are likely to affect their decisions more when dealing with smaller firms that have risk characteristics placing them near the lender's risk tolerance threshold. Larger firms also tend to take out larger loans and consume more banking services, yielding higher profit margins for lenders. If their discrimination is pure, lenders might be adequately compensated for lending to "distasteful" but relatively large customers. If discrimination is statistical, higher expected revenues might enable lenders to absorb the costs necessary to induce them to assess the risks of individual borrowers.

## THE REDLINING AND LENDING DISCRIMINATION LITERATURE

The bulk of the literature on redlining and lending discrimination has concerned residential mortgage lending, with much of it using data collected under the HMDA and related regulations. The availability of HMDA data and the historic focus of CRA and fair lending regulations on mortgage activity have spurred substantial research on residential lending patterns (Munnell et al. 1992; Wienk 1992; Kim and Squires 1995). The empirical literature on mortgage redlining can be categorized into two basic types: those focusing on an outcome-based definition of redlining and those focused on a process-based definition concerned with the approval or denial of formal applications (Yinger 1995). Outcome-based studies of lending flows, which focus on lending rates to different types of neighborhoods, were the norm before 1990, when the HMDA began to include microdata on loan applications, rather than only census tract summaries of originations (Bradbury, Case, and Dunham 1989; Hula 1991; Shlay 1988).

More recently, the mortgage access literature has focused on the approval or denial of formally submitted mortgage applications, in large part because the newer, publicly available HMDA data repeatedly have shown large disparities in approval rates by race, even after controlling for income. The bulk of this literature has focused on lending discrimination by race of applicant and less on a process-based definition of redlining, where the effect of the geographic location on approval rates is examined. In a study that spurred much of the recent lending discrimination literature, Munnell et al. (1992) found significant evidence of discrimination in loan approvals but no evidence of redlining in the approval process.

Yinger (1995) noted that the outcome-based studies often find evidence of redlining or differential flows of credit when controlling for neighborhood characteristics. The outcome-based studies are more difficult to model because they attempt to explain the results of a number of different current and historical processes, including the marketing and screening procedures of lenders and realtors, anticipated discrimination by potential home buyers, and historical discrimination. The process-based studies, on the other hand, merely attempt to isolate discrimination or redlining in the approval of formal loan applications, which is only one part of the lending process. Although these studies are easier to implement, the findings may be quite limited. If redlining occurs primarily through lenders not marketing their services in certain areas, for example, a process-based study finding no redlining in the approval process may be of limited relevance.

## DETERMINANTS OF BUSINESS LENDING

Before attempting to develop a model of small-business lending flows across urban space, some basic information on determinants of credit access is important. In a nongeographic, process-based study using data from the Federal Reserve Board's 1993 National Survey of Small Business Finances, Cole (1998) found that newer and smaller firms are more likely to be turned down for loans than older and larger firms. The Federal Reserve Board's Survey of Small Business Finances shows that wholesalers and manufacturers account for a disproportionate amount of commercial bank loans to small corporations (Federal Reserve Board of Governors 1997).

Using a survey of 1,300 firms, Ando (1988) found that black-owned firms are denied bank loans at significantly higher rates than white-owned firms. Similarly, from a survey of 448 firms in the Denver area, Ford (1996) found that black-owned firms are denied loans at 3.5 times the rate that white-owned firms are. After screening out firms not meeting minimum sales and net worth levels and three years of operating history, the denial rates for screened white firms are found to drop significantly, but denial rates for screened black firms do not. Both of these studies are likely to suffer from selection bias because firms rejected for bank loans and no longer in business are not included in the surveys. This bias suggests that the denial rate disparities in these studies may be underestimated.

In analyzing data from the characteristics of business owners (CBO) database, Bates (1989, 1993) found that banks make smaller loans to start-up firms located in minority areas than to firms in nonminority areas while controlling for financial equity, owner education, race, age, and experience. To compound the problem, he found that minority-owned start-up firms in minority areas tend to have smaller educational and financial equity endowments than other firms, resulting in even smaller loan sizes. In a more recent study, Bates (1997) again found that white-owned firms are able to attract larger amounts of debt than similarly situated black-owned firms.

## THE DATA

The data used here are collected by the Federal Financial Institutions Examination Council (FFIEC), a federal agency that coordinates common activities among the four federal banking regulators. Banks and thrifts with at least $250 million in assets or owned by a bank holding company with at least $1 billion in assets are required to report data aggregated by census tract on the number and dollar amount of loans to businesses, including subtotals by loan size (up to $100,000, $101,000 to $250,000, and $251,000 to $1,000,000) and by annual sales of business ($1,000,000 or less, more than $1,000,000).[5] The data reported to the FFIEC are not fully disclosed to the public. Aggregate levels for all reporting institutions are essentially fully disclosed, with a report providing the aggregate number and dollar amount of lending for all census tracts where loans are made. Bank-specific reports, however, do not provide tract-by-tract data.[6]

The FFIEC data do not include all lending to small firms. The small banks and thrifts not required to report these data accounted for approximately 35% of the outstanding business loans of $1,000,000 or less reported on the balance sheets of banks and thrifts in June 1996 (Bostic and Canner 1998). Moreover, data from the 1993 National Survey of Small Business Finances show that commercial banks accounted for 63% of outstanding loans, by dollar amount, to small nonfinancial corporations (Federal Reserve Board of Governors 1997). Finance companies constituted another 18%, with other sources accounting for the rest.[7]

To identify differences in intrametropolitan business lending rates, I analyzed loans of under $1 million to firms in the six-county Chicago metropolitan area from the 1996 FFIEC data. The Chicago area is economically diverse, with a broad distribution of neighborhood types and a diverse industrial mix. It is a region that, like many metropolitan areas, has experienced a shift in both the mix and location of employment in recent decades. Manufacturing jobs declined in the region in the 1970s, with losses being the greatest in the central city (Kasarda 1993). Up until 1990, at least, the geographic locus of employment has moved outward, especially toward the western and northwestern suburbs (Orfield 1997). In the national economic expansion of the mid-1990s, the Chicago area economy has fared particularly well, with the metropolitan unemployment rate generally falling between 0.1 to 0.6 percentage points below the national unemployment rate during 1996.

In the six-county Chicago area during 1996, banks and thrifts reported 24,182 loans to firms with annual sales of $1,000,000 or less in census tracts with nonzero residential populations.[8] Table 1 provides lending activity broken out by four neighborhood income categories for the Chicago area.[9] The table also breaks out the number of firms with sales of $1 million or less, as reported by Dun and Bradstreet, located in each type of tract in 1996. Also shown are loan-per-business rates in each of the four neighborhood income categories.

Table 1 shows that loan-per-firm rates are substantially higher in higher-income tracts than in lower-income tracts. The lending rate is 50% higher in

**TABLE 1: Small-Business Lending to Firms with Annual Sales of $1,000,000 or Less by Income of Census Tract in a Six-County Chicago Area, 1996**

| | *Income Level of Census Tract* | | | | |
|---|---|---|---|---|---|
| | *Low* | *Moderate* | *Middle* | *Upper* | *Total*[a] |
| Number of loans to firms with ≤ $1,000,000 in sales | 898 | 2,745 | 9,878 | 10,661 | 24,182 |
| Number of firms with ≤ $1,000,000 in sales | 8,347 | 20,645 | 65,160 | 65,776 | 159,928 |
| Loans per firm | 0.108 | 0.133 | 0.152 | 0.162 | 0.151 |

a. Total does not include loans or firms in tracts with unknown income level.

upper-income tracts than in low-income tracts and is 14% higher in middle-income tracts than in moderate-income tracts.

Dun and Bradstreet data are expected to undercount firms, especially smaller ones; those less likely to seek credit; or those operating primarily in the informal economy. It might be expected, therefore, that firms in lower-income and especially ethnic or immigrant neighborhoods would be less likely than those in more affluent areas to be included in the Dun and Bradstreet data. If this is the case, then the differentials in loan-per-firm rates shown in Table 1 would underestimate the actual differentials.

## MULTIVARIATE ANALYSIS OF GEOGRAPHIC LENDING PATTERNS

Both the demand and supply of loans in a geographic area are likely to depend on some variables that are difficult to observe, such as the credit history or revenue trends of local firms. Although unobserved variables and the aggregate form of the data preclude definitive conclusions about geographic or racial discrimination in marketing or approving loans, measuring intrametropolitan lending patterns while controlling for some important tract characteristics aids in the understanding of business financing. Moreover, such analysis helps to indicate the degree to which concern is warranted over access to business credit in lower-income areas and among minority-owned firms. In the near term, this has important implications for regulatory policy regarding the collection of more detailed business loan data.

Following the literature on business financing, a simple model of business lending activity in a small geographic area or neighborhood is suggested:

$$l_i = \alpha + \beta b_i + \gamma z_i, \qquad (1)$$

**TABLE 2: Variable Definitions, Names, and Summary Statistics: Chicago-Area Census Tracts, 1996**

| *Description of Variable* | *Variable Name* | *Mean* | *Standard Deviation* |
|---|---|---|---|
| Number of loans to firms with \$1,000,000 or less in annual sales (dependent variable) | Number of loans | 15.28 | 18.67 |
| Number of firms with \$1,000,000 or less in annual sales | Number of firms | 101.42 | 121.89 |
| Proportion of firms with five or more employees | Firm size | 0.35 | 0.11 |
| Proportion of firms in manufacturing | Proportion manufacturing | 0.07 | 0.07 |
| Proportion of firms in wholesale | Proportion wholesale | 0.08 | 0.05 |
| Proportion of firms in retail | Proportion retail | 0.21 | 0.10 |
| Median family income of residents | Neighborhood income | \$42,573 | \$19,807 |
| Proportion of residents who are black | Proportion black | 0.21 | 0.34 |
| Proportion of residents who are Hispanic | Proportion Hispanic | 0.13 | 0.20 |

where $l_i$ is the number of loans to businesses with \$1,000,000 or less in sales in tract $i$, and $b_i$ is the number of businesses with \$1,000,000 or less in sales in tract $i$. The vector $z_i$ is a set of tract characteristics, including the proportion of firms in manufacturing, wholesaling, and retailing sectors; the proportion of firms that are relatively large; tract income; and tract race and ethnicity.

The new CRA data allow for the estimation of equation (1), with the dependent variable equal to the number of loans made to small firms (those with sales under \$1,000,000) in a census tract during 1996. A complete description of dependent and independent variables is given in Table 2. The data set for estimating equation (1) was selected from the 1,738 census tracts with nonzero population in the six-county Chicago area. Because tracts with very few small firms might be expected to receive no small-business loans, such tracts were excluded from the analysis. As shown in Table 1, there were 0.151 loans made for each small business in the region. Thus, on average, one loan is expected for every 6.6 small firms. To ensure a reasonable, minimum number of small firms in every observation, 172 tracts with fewer than 13 small firms were excluded, leaving 1,566 observations.

Table 3 provides the results of an ordinary least squares (OLS) estimation of equation (1). Because heteroscedasticity is a common concern in cross-sectional geographic data sets, partial residual plots were examined. As might be expected, the plot of the partial residual for the number of firms (not shown here) strongly suggests heteroscedasticity, which results in biased standard error measurements. MacKinnon and White (1985) developed a

TABLE 3: Ordinary Least Squares (OLS) and Heteroscedastic-Robust Results (equation 1)

| | | Standard Error | |
|---|---|---|---|
| *Independent Variable* | *Coefficient* | *OLS* | *Heteroscedastic-Robust* |
| Number of firms | 0.1217 | 0.0018*** | 0.00721*** |
| Firm size | 8.9602 | 2.2200*** | 1.9895*** |
| Proportion manufacturing | 9.1053 | 3.8508** | 3.8722** |
| Proportion wholesale | 26.4533 | 4.8206*** | 4.8578*** |
| Proportion retail | –4.1845 | 2.411* | 1.9739** |
| Neighborhood income | $5.118 \times 10^{-5}$ | $1.474 \times 10^{-5}$*** | $1.554 \times 10^{-5}$*** |
| Proportion black | –2.6679 | 0.7783*** | 0.7050*** |
| Proportion Hispanic | –5.8537 | 1.3058*** | 1.1600*** |
| Constant | –3.3638 | 1.3170** | 1.2481*** |

NOTE: Dependent variable equals number of loans. $R^2 = 0.8154$; $N = 1,566$.
* Significant at 0.10. ** Significant at 0.05. *** Significant at 0.01.

covariance matrix for OLS estimates that is robust to heteroscedasticity. Following Anselin (1995), the results of an adjusted-white OLS estimation using these estimates are presented in the right-hand columns of Table 3. This procedure does not affect the coefficient estimates but does result in different standard errors. Significance levels for the heteroscedastic-robust results are based on *z*- and not *t*-statistics.

The results of the heteroscedastic-robust estimation indicate that all independent variables are significant at the 0.01 level, except for proportion manufacturing and proportion retail, which are significant at the 0.05 level. The signs of all coefficients are as expected. Other things equal, areas with relatively large businesses (firm size) are expected to receive more loans, which is consistent with Cole (1998). Tracts with more wholesalers and manufacturers and with fewer retailers are expected to see more lending, with proportion wholesale having the stronger effect.

Higher median incomes and lower proportions of minority residents also lead to higher numbers of small-business loans. Other things held constant, going from a low-income neighborhood with a 1989 median family income of $20,000 to an upper-income neighborhood with a median income of $60,000, for example, is expected to result in an increase of two small-business loans. Given an average number of small-business loans of 15.3, this is a significant effect. The effect of proportion Hispanic has a large effect on lending activity. Going from an all-white to an equivalent all-Hispanic neighborhood is expected to result in a decrease of 5.9 small-business loans. Going from an all-white to an all-black neighborhood is expected to result in a decrease of 2.7 loans. It should be pointed out, however, that the standard deviation of proportion black (0.35) is significantly higher than that of proportion Hispanic (0.20), so that difference in standardized coefficients (not shown here) for these two variables is not as large as the difference in unstandardized coefficients.

In many large cities, sizable changes in neighborhood income are typically accompanied by significant racial change. Combining the effects of income and racial change show substantial effects on business lending volumes. Going from an all-white tract with a 1989 median income of $60,000 to an otherwise similar all-Hispanic tract with a median income of $20,000 is expected to result in a drop in the number of loans by 7.9 loans. Given a mean of 15.3 loans, this is a very large decrease. Similarly, an all-black neighborhood with an income of $20,000 is expected to see 4.7 fewer loans than a similarly situated all-white tract with a median income of $60,000.

The results in Table 3 can be criticized for failing to account for the problem of spatial autocorrelation, which occurs when the regression residuals of a pair of nearby observations are more similar than those of more distant pairs and can result in biased coefficient estimates. As explained in the appendix, I use a spatial lag model to account for spatial autocorrelation. This model accounts for the lending levels of other neighborhoods within a distance of approximately 7 miles and weights these neighboring observations by an inverse distance function, following the gravity model of spatial interaction.

The results of a two-stage least squares estimation of this model are given in Table 4. Two different specifications of the spatial lag function are estimated, as explained in the appendix. The signs of all coefficients remain unchanged from the OLS results in Table 3. Moreover, for variables including the number of firms, firm size, proportion manufacturing, and proportion wholesale, coefficient magnitudes are similar to the OLS results of Table 3, and significance levels remain the same. Coefficient magnitudes for proportion retail, neighborhood income, proportion black, and proportion Hispanic do decline significantly compared to Table 3. Controlling for spatial lag correlation yields results in which proportion retail is no longer significant, and the significance of proportion black depends on the precise specification of the spatial lag variable.

The results in Table 4 do not suggest a reduced effect of location on lending activity. Rather, they merely indicate that race and income alone do not fully describe a neighborhood's locational predisposition for lending volume. A white neighborhood surrounded by many minority neighborhoods with low lending volume is expected to see lower lending activity than a white neighborhood surrounded by other white neighborhoods with high

**TABLE 4: Two-Stage Least Squares Estimation of the Spatial Lag Model Using Inverse Distance Squared and Cubed Weighting ($N = 1,566$)**

| | *Inverse Distance Squared (k = 2)*[a] | | *Inverse Distance Cubed (k = 3)*[a] | |
|---|---|---|---|---|
| *Independent Variable* | *Coefficient* | *Standard Error* | *Coefficient* | *Standard Error* |
| Spatially lagged number of loans | 0.2245 | 0.0351*** | 0.1297 | 0.0301*** |
| Number of firms | 0.1224 | 0.0019*** | 0.1233 | 0.0019*** |
| Firm size | 9.0385 | 2.1299*** | 8.5440 | 2.1573*** |
| Proportion manufacturing | 8.9826 | 3.6951** | 9.1574 | 3.7389** |
| Proportion wholesale | 21.5413 | 4.6889*** | 24.0620 | 4.7133*** |
| Proportion retail | −2.2109 | 2.3344 | −2.8617 | 2.3614 |
| Neighborhood income | $2.283 \times 10^{-5}$ | $1.459 \times 10^{-5}$* | $3.657 \times 10^{-5}$ | $1.47 \times 10^{-5}$** |
| Proportion black | −1.0271 | 0.7896 | −1.752 | 0.7850** |
| Proportion Hispanic | −3.7460 | 1.2955*** | −4.593 | 1.3012*** |
| Constant | −5.7379 | 1.3170*** | −4.467 | 1.3042*** |
| Goodness-of-fit measures[b] | | | | |
| Pseudo-$R^2$ | 0.8248 | | 0.8206 | |
| Correlation squared | 0.8201 | | 0.8177 | |

a. For explanation of inverse distance squared and cubed specifications, see the appendix.
b. A traditional $R^2$ is not applicable to this instrumental variables approach (Anselin 1988, 1995). The pseudo-$R^2$ is equal to the ratio of the variance of predicted values of the dependent variable to the variance of the observed values of the dependent variable. Also shown is the square of the correlation between the predicted and observed values of the dependent variable. These are not directly comparable to the ordinary least squares $R^2$ in Table 3.
* Significant at 0.10. ** Significant at 0.05. *** Significant at 0.01.

lending activity. This is consistent with the fact that bank branches, which tend to be located in middle- and upper-income areas, serve larger areas than single census tracts. Thus, the demographics of surrounding areas may be an important determinant of a neighborhood's lending level. To interpret the effects of neighborhood race and income, then, the spatial lag variable must be held constant. Because most lower-income and minority neighborhoods are situated near other lower-income and minority neighborhoods, their spatial lag variables will tend to have relatively low values. Thus the race, ethnicity, and income coefficients in Table 4 are conservative measures of race and income effects because they measure only the independent impact of the neighborhood's demographics and not the effects of the demographics of nearby neighborhoods, which are now captured in the coefficient of the spatial lag variable.

Even after holding lending in surrounding areas constant, neighborhood income has a positive effect on small-business lending. A $40,000 increase in the median family income of a neighborhood is expected to result in between 1.1 and 1.4 more loans in otherwise similar neighborhoods. At the mean of 15.3 loans, this represents a 7% to 10% increase in lending volume. Going from an all-white to an equivalent all-black tract is expected to result in a decrease of 1 to 1.8 loans, approximately 7% to 12% at the mean, although the precise specification of the distance lag ($k = 2$ vs. $k = 3$) affects whether the result remains statistically significant. Finally, going from an all-white to an equivalent all-Hispanic tract is expected to result in a decrease of 3.7 to 4.6 loans, or a 24% to 30% reduction at the mean.

Again, changes in race and income tend to occur simultaneously across neighborhoods. Going from an all-white tract with a $60,000 median income to an otherwise equivalent all-black tract with a $20,000 median income is expected to result in a decrease of 2.1 to 3.2 loans, equal to a 14% to 21% reduction at the mean of 15.3 loans, holding lending in surrounding areas constant. A similar comparison to an all-Hispanic tract with a $20,000 median income would result in an expected decrease of 4.8 to 6 loans, or a 31% to 39% decrease at the mean.

The effect of proportion Hispanic on lending volume is particularly strong and of special concern. From a survey of mostly 235 small firms in the predominantly Mexican-American neighborhood of Little Village in Chicago, Bond and Townsend (1996) concluded that firms in the survey, most of which are Hispanic owned, were credit constrained in their start-up financing. They suggested that bank loans may be too inflexible for such firms, although they do not provide strong evidence for this conclusion. They also found that the Hispanic firms that had applied for a loan experienced a rejection rate of at least 44%. Thus it is not clear the extent to which low lending activity in such areas is due to cultural affinity issues, overt discrimination or redlining, or inappropriate credit vehicles. It seems likely, however, that cultural and language barriers between loan officers and business owners, especially recent immigrants, create barriers to credit. Research in mortgage lending provides some evidence of cultural affinity barriers, at least in the case of black mortgage applicants. Kim and Squires (1995) found that thrifts with higher proportions of black staff approve loans to blacks at higher rates.

As with the denial rate studies reviewed earlier, the omission of loan applicants who are no longer in business or were never able to start up is a problem of selection bias, so that patterns of loans originated may underestimate any problems of poor access to credit. On the other hand, the inability to fully measure firm demand across space may suggest bias in the other direction.

## LOWER-INCOME AND MINORITY AREAS SUFFER LOWER LENDING RATES

The new CRA data on small-business loans provide, for the first time, a description of the flow of small-business loans to different types of neighborhoods. Although these data are not adequate to confirm the existence of lending discrimination, lower-income and minority areas suffer from lower lending rates than higher-income and white neighborhoods, after controlling for industrial mix, firm size, and firm population. The negative effect of the proportion of residents who are Hispanic on lending volume is particularly strong. More research is needed to explain the low lending levels in low-income, black, and especially Hispanic areas.

These findings have important implications for both CRA and fair lending policies. Under the revised CRA regulations, examiners are now expected to assess the geographic patterns of banks' small-business as well as residential loans. The results presented earlier, as well as the available evidence on small-business access to credit, suggest the need for regulators to take this charge seriously. Moreover, under the Equal Credit Opportunity Act, banks are prohibited from discriminating on the basis of race. The Department of Housing and Urban Development and the Department of Justice have investigated mortgage lenders for fair lending violations. Similar investigations, including the use of matched-pair testing, could be used to identify lenders who discriminate in small-business lending. Such investigations are made more difficult, however, by the lack of racial and loan application data, which would enable investigators to identify banks that are more likely to be guilty of discrimination.

Better data are needed that can be regularly examined to measure and explain business lending activity in lower-income and minority neighborhoods. Bank regulators should collect and disclose HMDA-like microdata on small-business loan applications, including details such as approvals, loan purpose, firm size, industry, and race of owner. Although even HMDA-like data are unlikely by themselves to provide definitive evidence of discrimination, because of the inevitable omission of some relevant firm characteristics, they would provide much stronger suggestive evidence and could be used to spot potential violators of CRA and fair lending laws. Other data sets are available for research studies of discrimination. The CRA data, however, are the only data with bank-specific information on where institutions lend.

## APPENDIX
## Spatial Autocorrelation and the Spatial Lag Model

Two forms of spatial autocorrelation are of concern in the estimation of equation (1): spatial error and spatial lag. Ignoring spatial error correlation does not affect the consistency of estimators, only their efficiency (Anselin 1988). Given the large size of the data set here, a consistent estimator is sufficient. On the other hand, ignoring spatial lag correlation, in which the dependent variable is correlated with the dependent variable of nearby observations, results in inconsistent, biased estimators. Anselin (1995) provided two diagnostic tests for spatial lag correlation, both of which are significant at below $p = 0.01$ for the OLS estimation of equation (1).

To account for spatial lag effects, a spatially lagged dependent variable is added to equation (1):

$$l_i = \alpha + \rho\lambda_i + \beta b_i + \gamma z_i, \tag{2}$$

where $\lambda$ is a spatially lagged value of the number of small-business loans, $l$, and $\rho$ is the spatial autoregressive coefficient and expected to be positive.

Because census tracts vary greatly in size over the metropolitan area, the calculation of the spatial lag requires careful specification. Anselin (1988) suggested a variety of spatial lag methods, including immediate adjacency, distance contiguity, and inverse distance contiguity, in which spatial weights are assigned to observations within a cutoff distance in some form of inverse proportion to their distance from the observation of interest. The large size of some tracts in the Chicago area means that to ensure that all observations are "connected" to at least one other contiguous tract, the cutoff distance must be at least 6.94 miles, a relatively large radius. Using this large of a cutoff distance suggests the need for an inverse distance contiguity scheme, in which closer tracts are given more weight than more distant tracts. In such a scheme, the spatially lagged dependent variable, $\lambda$, is given by

$$\lambda_i = \sum_{j=1}^{m} \left( {}^{l}\!/\!{}_{d_{ij}^{k}} \right), \tag{3}$$

where $d_{ij}$ is the distance between observations $i$ and $j$, $m_i$ is the number of observations within the cutoff distance from observation $i$, and $k$ is some positive exponent. Weights are calculated, and lagged variables are computed for all observations within a specified cutoff radius. The simple gravity model would suggest $k = 2$, but the results of the estimation of equation (2) may be sensitive to the value of $k$.

A direct approach to estimating equation (2) would involve directly calculating the spatially lagged variable, $\lambda$, from equation (3). However, for large data sets, the use of directly calculated spatial lag variables often causes computational problems in maximum likelihood estimation (Anselin 1995). For large data sets, an instrumental variables approach can be used for estimating the spatial lag model. The inverse distance contiguity matrix is used to derive lagged values of each independent variable, and then those variables are used as instruments for the lagged dependent variable, $\lambda$.

Table 4 shows the results of a two-stage least squares estimation of equation (2), with the lagged independent variables used as instruments for the lagged number of loans. Two sets of results are presented. The first two columns give the results for equation (2) using the inverse distance squared form of equation (3), with $k = 2$. The last two columns provide results for the inverse distance cubed form, with $k = 3$.

## NOTES

1. Although lending discrimination is prohibited under the Equal Credit Opportunity Act, the Community Reinvestment Act (CRA) does not explicitly cover discrimination against individuals or minority groups, only the geographic patterns that might be caused in part by individual-based discrimination.

2. Beginning in 1990, Home Mortgage Disclosure Act (HMDA) data have included application-by-application data on the purpose and type of loan, loan amount, outcome of the application (approved, denied, withdrawn, etc.), and race, gender, and income of the applicant.

3. All banks and thrifts with assets of at least $250,000 or whose parent holding company has assets of at least $1 billion must report all business loans of $1,000,000 or less. Such loans are typically referred to as "small-business loans" by bank regulators but are actually better described as small loans to businesses because loans to businesses of any size are reported.

4. Even the much more detailed HMDA data are not complete enough to discern discrimination in the loan approval process. Supplemental loan file data are needed for such work. At the same time, the HMDA data by themselves are much more powerful in suggesting potential discrimination than are the CRA business loan data.

5. The Federal Financial Institutions Examination Council (FFIEC) uses error-checking algorithms to spot likely errors. Also, if borrowing firms only provide post office boxes, the tract of the post office is used as the location of the firm. The extent of this problem is not clear because the number of loans for which post office locations were used is unknown. See Bostic and Canner (1998) for further discussion of data issues.

6. Instead, bank-specific reports provide a distributional report for each county where a bank made loans during the year. These reports break lending volumes out into different neighborhood income ranges, such as low, moderate, middle, and upper income. Finer breakdowns are provided for larger counties.

7. Firms also may borrow from friends and family or through consumer credit cards. Business credit cards are included in the data.

8. These figures actually include both loans originated and purchased by reporting institutions. Purchases are not broken out for loans to firms with sales of $1 million or less. However, more than 97% of all loans in the six-county area are purchased, and this ratio is likely to be even higher in considering only loans to firms with sales of $1 million or less.

9. Income categories follow CRA categories and are determined by whether the tract's median family income falls within 0% to 49% of metropolitan median family income (low

income), 50% to 79% (moderate income), 80% to 119% (middle income), or 120% or greater (upper income) (U.S. Department of the Treasury 1995).

## REFERENCES


Anselin, L. 1988. *Spatial econometrics: Methods and models*. Boston: Kluwer.

———. 1995. *Spacestat version 1.80 users' guide*. Morgantown: Regional Research Institute, West Virginia University.

Ando, F. 1988. *An analysis of access to bank credit*. Los Angeles: Center for Afro-American Studies, University of California at Los Angeles.

Bates, T. 1989. Small business viability in the urban ghetto. *Journal of Regional Science* 29:625-43.

———. 1993. *Banking on black enterprise: The potential of emerging firms for revitalizing urban economies*. Washington, DC: Joint Center for Political and Economic Studies.

———. 1997. Unequal access: Financial institution lending to black- and white-owned small business start-ups. *Journal of Urban Affairs* 19:487-95.

Bingham, R., and Z. Zhang. 1997. Poverty and economic morphology of Ohio central city neighborhoods. *Urban Affairs Review* 32:766-96.

Bond, P., and R. Townsend. 1996. Formal and informal financing in a Chicago ethnic neighborhood: Economic perspectives. *Federal Reserve Bank of Chicago*, July, 3-27.

Bostic, R., and C. Canner. 1998. New information on lending to small businesses and small farms: The 1996 CRA data. *Federal Reserve Bulletin*, January, 1-21.

Bradbury, K., K. Case, and C. Dunham. 1989. Geographic patterns of mortgage lending in Boston, 1982-1987. *New England Economic Review*, September/October, 3-30.

Cole, R. 1998. The importance of relationships to the availability of credit. *Journal of Banking and Finance* 22:959-77.

Dymski, G. 1996. Business strategy and access to capital in inner-city revitalization. *Review of Black Political Economy* 24 (2/3): 51-66.

Federal Financial Supervisory Agencies. 1993. Joint notice of proposed rulemaking: Community Reinvestment Act regulations. *Federal Register*, 21 December (58 FR67466).

———. 1994. Joint notice of proposed rulemaking: Community Reinvestment Act regulations. *Federal Register*, 7 October (59 FR51232).

Federal Reserve Board of Governors. 1997. *Report to the Congress on the availability of credit to small businesses*. Washington, DC: Author.

Ford, F. 1996. *Survey of small business lending in Denver*. Denver: Colorado Center for Community Development, University of Colorado at Denver.

Hula, R. 1991. Neighborhood development and local credit markets. *Urban Affairs Quarterly* 27:249-67.

Hunter, W. C., and M. B. Walker. 1995. *The cultural affinity hypothesis and mortgage lending decisions*. Federal Reserve Bank of Chicago Working Paper Series No. 95-8. Chicago: Federal Reserve Bank of Chicago.

Kasarda, J. 1993. Urban industrial transition and the underclass. In *The ghetto underclass: Social science perspectives*, edited by W. J. Wilson, 43-64. Newbury Park, CA: Sage.

Kim, S., and G. Squires. 1995. Lender characteristics and racial disparities in mortgage lending. *Journal of Housing Research* 6:99-113.

Lang, W., and L. Nakamura. 1993. A model of redlining. *Journal of Urban Economics* 33:223-34.

MacKinnon, J., and H. White. 1985. Some heteroscedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics* 29:305-25.
Munnell, A., L. Browne, J. McEneaney, and G. Tootel. 1992. *Mortgage lending in Boston: Interpreting HMDA data*. Working Paper No. 92-7. Boston: Federal Reserve Bank of Boston.
Orfield, M. 1997. *Metropolitics: A regional agenda for community and stability*. Washington, DC: Brookings Institution.
Porter, M. 1995. The competitive advantage of the inner city. *Harvard Business Review*, May/June, 55-71.
Shlay, A. 1988. Not in that neighborhood: The effects of population and housing on the distribution of mortgage finance within the Chicago SMSA. *Social Science Research* 17:137-63.
U.S. Department of Housing and Urban Development. 1995. *Empowerment: A new covenant with America's communities: President Clinton's national urban policy report*. Washington, DC: Author.
U.S. Department of the Treasury. 1995. *Community Reinvestment Act regulations and home mortgage disclosure: Final rules*. Office of the Comptroller of the Currency, 12 CFR Part 25. Washington, DC: Author.
Wienk, R. 1992. Discrimination in urban credit markets: What we don't know and why we don't know it. *Housing Policy Debate* 3:217-40.
Yinger, J. 1995. *Closed doors, opportunities lost: The continuing costs of housing discrimination*. New York: Russell Sage.

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