A TALE OF TWO CITIES: RACIAL AND ETHNIC GEOGRAPHIC DISPARITIES IN HOME MORTGAGE LENDING IN BOSTON AND PHILADELPHIA

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In Home Mortgage Lending in Boston and Philadelphia

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Abstract

Recent data released pursuant to the 1989 amendments to the Home Mortgage Disclosure Act (HMDA) which show large disparities in mortgage lending between minority and non-minority neighborhoods, have refocused the attention of policy makers, lenders, community advocates and academics on possible racial discrimination in the home loan market. In this paper, we review the existing literature on redlining. Many of the methodological shortcomings of previous studies can be remedied by using post-1989 HMDA data to examine whether lender acceptance or rejection of mortgage applications is related to racial and ethnic neighborhood composition. We test two models of the lender's decision to accept or reject loan applicants, one including and one without variables that proxy for neighborhood risk using data for Boston and Philadelphia. With proxies for neighborhood risk included, the results do not support the hypothesis that financial institutions redline neighborhoods in these two cities.

A Tale of Two Cities:
Racial and Ethnic Geographic Disparities in Home Mortgage Lending in Boston and Philadelphia

Michael H. Schill and Susan M. Wachter*

In recent years, federal housing policy has increasingly focused on promoting homeownership among low income households (DiPasquale 1990, Schill 1990). In particular, legislation has been enacted to encourage low income, predominantly minority families living in central cities to become homeowners (Cranston-Gonzalez National Affordable Housing Act 1990). Despite these efforts, recent empirical studies show large disparities in homeownership rates between whites and blacks. In 1989, the proportion of white households that were homeowners exceeded the homeownership rate among nonwhite households by twenty percentage points, a disparity that has persisted for two decades (Wachter and Megbolugbe 1992).

Disparities in homeownership rates between white and nonwhite households are caused by economic as well as non-economic factors.[1] On average, racial minorities earn less

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income than whites and possess less wealth (Wachter and Weicher 1989). In addition, recent housing audits indicate that minority home buyers are discriminated against by sellers and real estate agents (Turner, Struyk and Yinger 1991). Finally, many have alleged that home loan mortgage originators systematically discriminate against nonwhite applicants either individually or by denying credit to the neighborhoods they live in through a process identified as "redlining"[2] (Dreier 1991).

Whether mortgage originators redline predominantly minority neighborhoods has enormous significance for public policy. Arbitrary denial of credit may harm individual applicants who are discouraged from owning homes. Denial of mortgage credit to entire neighborhoods may lead to disinvestment in these communities and the deterioration of living conditions for their inhabitants. In this article, we seek to determine whether a relationship exists between the granting of home mortgage loans by financial institutions in Boston and Philadelphia and the racial composition of neighborhoods in which applicants wish to live.

In the mid-1970s, Congress acted to fight what it believed to be discriminatory lending practices by home loan mortgage originators. The Home Mortgage Disclosure Act of 1975 (HMDA) requires lenders to disclose the location by census tract, number and amount of mortgage loans they originate. The Community Reinvestment Act of 1977 (CRA) imposes an affirmative obligation on lenders to meet the credit needs of all residents in their service areas. Financial institutions that do not meet their CRA obligations will be denied federal approval of their applications to acquire or merge with other institutions or to engage in other businesses.

Prior to 1990, data made available under HMDA included only the aggregate number of loans and the dollar value of the loans originated in individual tracts. Studies using this data, by necessity, were unable to isolate whether the amount of loans originated in a particular neighborhood was determined by the forces of supply or demand. For purposes of determining whether banks redline, however, one must be able to isolate and ascertain the factors that affect the supply decision. In 1989, as part of the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA), Congress attempted to address the shortcomings of HMDA by requiring mortgage originators to provide data to federal regulatory agencies on whether they accepted or rejected individual applicants by census tract. Loan originators must also report the applicants' income, sex and race. Post-1989 HMDA data, by including information on whether individual applicants are accepted or rejected, permit us to study separately the determinants of the supply decision.

Together with recent journalistic reports of geographic discrimination in the home loan mortgage market (Dedman 1988), newly released HMDA data have refocused the attention of policy makers, lenders, community advocates and academics on possible racial discrimination in the home loan mortgage market. These data show large disparities in the rates of acceptance between white and nonwhite applicants for mortgage loans as well as between minority and non-minority neighborhoods (Canner and Smith 1991, 1992).

In response to this new evidence of higher rejection rates in predominantly minority areas, consumer advocates and community groups have called for increased enforcement of existing legal protections against home finance discrimination. In particular, there have been calls for enhanced review of lenders' performance under the Community Reinvestment Act (CRA). One of the primary reasons for passage of the Act was to deter banks from redlining inner city communities disproportionately composed of minority households.

The release of the newly constituted HMDA data permit us to better understand the relationship between the racial and ethnic composition of neighborhoods and home mortgage lending decisions. In this paper, we specify models to test whether the racial and ethnic composition of the geographic area in which loan applicants wish to purchase, refinance or improve their homes is related to lenders' decisions to accept or reject their applications. A test of whether lenders discriminate based upon the race or ethnicity of individual applicants is impossible because the HMDA data do not contain controls for borrower creditworthiness and default risk.

The paper is organized as follows: Part I reviews the empirical literature on home mortgage redlining. In Part II we model the accept/reject decision as a function of borrower characteristics and economic factors and include geographic racial and ethnic concentration ratios to test for disparate lending patterns. Part III describes the data used in the estimated models. In Part IV we present and discuss the results of our empirical analysis.

I. Previous Research on Redlining

Most studies that test for the existence of redlining use one of two methodologies. One set of studies (the "Aggregate Studies") examines the aggregate supply of home mortgage loans made in particular neighborhoods to determine whether the racial composition of these communities is related to the number of loans or amount of funds made available by lending institutions. The second set of studies (the "Accept/Reject" Studies) examines the relationship between the racial composition of neighborhoods and the probability that applications for home loans are accepted or rejected in those neighborhoods. Table 1 summarizes the results of Aggregate and Accept/Reject Studies, describing the data used, methodology, level of geographic aggregation, dependent variables, control variables and the measure(s) used to test for possible redlining.

Aggregate Studies typically specify three sets of independent variables. The first set is included to measure demand for mortgage credit; the second set is included to capture the risk of loss to the lender. Third, indicators of possible redlining are included. Accept/Reject Studies typically include the latter two sets of variables.

Table 1 contains the results of six Aggregate Studies completed before 1982. All but one (Listokin & Casey 1980) find inconsistent results. The single early Accept/Reject Study (Schafer & Ladd 1981) finds little evidence of redlining.

A. Recent Aggregate Studies

Table 1 summarizes the results of four recent Aggregate Studies. Three examine lending patterns in individual metropolitan areas or cities: Baltimore (Shlay 1989), Boston (Bradbury et al 1989) and Chicago (Shlay 1988). Each area-specific study finds evidence of geographic racial and ethnic disparities consistent with the hypothesis of redlining. The only recent study which does not consistently support the hypothesis of redlining, Hula (1989), has been criticized for using aggregate data for the entire United States.[3]

All three area-specific studies are consistent in their findings that financial institutions redline minority neighborhoods. Nonetheless, all of these Aggregate Studies are subject to the same methodological problem. Because the studies use reduced form equations, they cannot identify coefficients of racial concentration variables as reflecting supply rather than demand influences. The use of reduced form equations which combine demand and supply factors result in geographic racial and ethnic concentration measures that reflect demand-side influences, although they are included to test for lender discrimination (Galster 1992b).

B. Recent Accept/Reject Studies

Guttentag and Wachter (1980) and Ostas (1982) suggest the use of Accept/Reject Studies as a way to remedy the methodological shortcomings of Aggregate Studies. Prior to 1991, only one Accept/Reject Study had been published (Ladd & Schafer 1981). The primary reason is that data released under HMDA did not contain information about individual loan applicants. As a result of the 1989 amendments to HMDA these data are now available. Three recent studies, all using post-1989 HMDA data, have examined whether racial and ethnic geographic disparities exist in mortgage lending. Two studies by Canner and Smith (1991, 1992) report the disposition of home loan applications by the purpose of the loan and the racial characteristics of the census tracts in which the properties were located. The data, which cover all metropolitan areas in the United States, show that approval rates for households wishing to purchase homes in predominantly minority census tracts are considerably lower than approval rates elsewhere.

A third study that utilizes HMDA accept/reject data (Munnell et al. 1992) extensively tests for discrimination against individual applicants based upon race. Although redlining is not a central focus of their study, the authors present one model with a geographic racial composition variable measuring whether a neighborhood has a population that is more than 30% black. The study finds that the coefficient for this variable is statistically insignificant.

Existing Accept/Reject Studies do not adequately test whether geographic racial and ethnic disparities exist in the home loan mortgage market. Canner and Smith (1991, 1992) do not conduct multivariate analysis; their study is limited to crosstabulations. Schafer and Ladd (1981) and Munnell et al. (1992) include few neighborhood risk variables in their studies.

The models presented in this article use the Accept/Reject methodology to examine whether geographic racial and ethnic disparities in home mortgage lending exist in two large American cities: Boston and Philadelphia. The use of an Accept/Reject model permits us to identify separately the effects of supply and demand. Furthermore, we control for neighborhood risk by using extensive data from the 1990 Census of Population and Housing.

II. Methodology

In this section we use a simple framework to examine the effect of racial and ethnic minority neighborhood composition on loan acceptance rates. For each of three loan types (home purchase, refinancing, and home improvement loans), we specify two alternative Accept/Reject models (with and without neighborhood risk proxies) to test whether the racial and ethnic composition of geographic areas in which applicants seek conventional home mortgage loans are related to the decision by lenders to accept or reject their loan applications. Our analysis focuses on conventional rather than FHA- or VA-insured mortgages because previous studies suggest that racial discrimination is more likely to affect the origination decisions of the former (Canner, Gabriel & Wooley 1991, Gabriel and Rosenthal 1991).

We model financial institutions' mortgage lending decisions by hypothesizing that these decisions are a function of risk and return factors that affect the expected net present value of the loan. In the absence of discrimination,[4] to maximize profits, financial institutions are assumed to accept loan applications whenever a loan's expected net present value (NPV) exceeds zero.

The probability that an individual applicant in a particular census tract is accepted for a mortgage loan is described as follows:

$$\text{Prob }(P)_{ij} = f(I_i, C_j)$$

where P_{ij} is the probability that a mortgage loan application by individual i for a dwelling unit in census tract j is accepted; I_i and C_j are sets of individual loan application and census tract characteristics, respectively, which are hypothesized to affect NPV. P=1 if the loan application is accepted and P=0 if the application is rejected.

The analysis employs a standard logit regression model to estimate the probability that a borrower will be accepted for a loan:

$$P=\exp [BX]/(1+\exp[BX])$$

where P represents the probability of acceptance for a loan with characteristics X and X is a vector of the attributes of the loan, including sets of borrower and location characteristics I_i and C_j. The vector of estimated coefficient values B indicates the effects of each characteristic on the likelihood of acceptance. The modeling of lenders' accept/reject decisions in this form assumes that the separation of the sample into accepted and rejected applications is only the lender's decision (Maddala & Trost 1982).[5] Furthermore, the mortgage interest rate is assumed to be set by market conditions and financial institutions' willingness to bear risk. (Stiglitz & Weiss 1981). The acceptable level of risk is determined by secondary market and lending institutions. These institutions prescribe sets of standards (related to risk) above which they will purchase or originate loans for a given return.

The empirical specification of the above model uses measures of borrower and location characteristics that are hypothesized to affect the loan's NPV through their expected impact on mortgage loss attributable to default. This expected loss is, itself, a combined function of the likelihood of default and the expected loss upon default.

We next consider the expected effects of the individual and neighborhood risk proxies in our model on the lenders' accept/reject decisions. The economic literature on mortgage defaults shows that individual borrower characteristics may or may not be related to the risk of default (Stegman & Quercia 1992). We employ all individual borrower characteristics contained in the HMDA loan register including the applicant's race, ethnicity, income and sex in our first specification, Model 1. In addition, we use HMDA data to construct a loan constraint variable that we expect will be negatively related to the probability of loan acceptance (Linneman & Wachter 1989).

We also include as an individual characteristic in Model 1 the size of the loan requested. A lender's decision to accept or reject a potential borrower may be related to the size of the loan requested although the direction of the relationship is unclear. Ceteris paribus, lenders may prefer to originate larger loans to those that are small because of economies of scale in loan production. On the other hand, the loss upon default is likely to increase with the size of the loan.

The use of publicly available data limits our access to individual borrower and property risk characteristics. In particular, we lack borrower credit history. Because we lack detailed borrower characteristics, we cannot interpret the race or ethnicity of the borrower as a measure of individual race discrimination. We thus test for disparate lending patterns assuming that financial institutions do not discriminate on the basis of individual borrower characteristics. Alternatively, if financial institutions do so discriminate, we test for whether the racial or ethnic composition of neighborhoods has an additional negative impact on loan acceptance rates.

In our second model (Model 2), we add to the individual applicant variables of Model 1, variables that proxy for neighborhood risk. Empirical studies of the determinants of mortgage default (Quercia and Stegman 1992) consistently find that the loan-to-value ratio at the time of default is the critical factor in whether borrowers exercise their default option. To minimize expected mortgage loss, financial institutions must, ex ante, predict whether the expected future value of the property securing the loan will exceed the outstanding debt.

Because we rely solely on publicly available data, we are unable to include in our model a number of property-related risk characteristics that lenders often use in their underwriting decisions. Most critically, we lack loan-to-value ratios at the time of loan application as well as during subsequent periods since we do not have the appraised value of the property.[6] Nonetheless, we are able to include neighborhood risk proxies that are likely to affect future loan-to-value ratios.

The economic literature indicates that declines in home values in particular geographic areas are likely to be correlated because of the existence of externalities.[7] The decision by individual homeowners not to maintain their homes reduces the value of these homes. Because of externalities, these individual decisions to disinvest reduce land values in the community. Lower property values, in turn, reduce the incentives of neighboring homeowners to maintain their homes. Homeowners will not invest in physical repairs because they will be unable to recapture the value of their investments due to decreased sales prices.

A household's ability to maintain its home is correlated with its financial capacity. Homeowners with lower incomes are less able than more affluent residents to invest in repairs and improvements (Linneman & Wachter 1989, Gyourko & Linneman 1993). Moreover, the income elasticity of demand for housing is lower for low income households (Ihlanfeldt 1982). In addition, Potepan (1989) finds that the propensity to move rather than engage in home improvement increases with household income. As a result, the level of disinvestment in a particular neighborhood may be negatively related to the income of its residents. In particular, neighborhoods with high proportions of very low income households may experience significantly higher levels of capital consumption. To capture the effects of income and poverty we include in our model two variables: median household income and the proportion of households receiving public assistance.

Homes that have either not been maintained in the past or that currently require high levels of repair are especially likely to deteriorate because greater costs of maintenance deter homeowners from investment (Galster 1987). These homes are also more likely to generate negative externalities when the owner disinvests. Since older homes are often in worse physical condition than new homes and are more costly to repair, we expect that the age of housing in a neighborhood will be positively related to the risk of disinvestment.[8] A lack of adequate maintenance of housing is also more likely to occur when structures are occupied by tenants rather than homeowners. Due to agency costs, homes are more likely to be well maintained when the owner is in possession.[9] Neighborhoods with higher levels of homeownership are thus less likely to experience disinvestment. In our model, we attempt to capture these dynamics by including variables that measure the median age of homes in the neighborhood as well as the proportion of homeowners.

Disinvestment is also more likely to occur in neighborhoods with high levels of vacant housing units.[10] Vacant units and low house values may reveal expectations of property owners that the opportunity cost of continued investment in that community is not justified.[11] These lower expectations of capital gains would also be indicated by higher rent-to-value ratios.[12] To capture these effects we include in Model 2 vacancy rate, median house value and rent-to-value ratio variables.

Finally, we include variables to measure the proportion of households in each census tract in 1990 that are headed by persons designated as black and Hispanic. These variables are used in both Models 1 and 2 to test for disparate lending patterns based on the racial and ethnic composition of the geographic area.

III. Description of Data

Two sources of data are used in this study. Data on the individual characteristics of applicants for mortgage loans and their success or failure in obtaining these loans is provided by the Federal Financial Institutions Examination Council (FFIEC). Under HMDA, all lending institutions located within a metropolitan statistical area with assets in excess of ten million dollars are required to file loan registers with the FFIEC in which they report for each mortgage loan applicant the type of loan they applied for (i.e. conventional or federally insured), the purpose for the loan (i.e. home purchase, home improvement, refinance or multi-family dwelling), the dollar amount of the loan, the census tract in which the dwelling securing the loan is located, whether the dwelling is owner-occupied and whether the loan application was approved or denied. The HMDA disclosure records also provide information on the applicant's income, sex and race.

To estimate our models, we use HMDA data on applicants for conventional home mortgage loans.[13] The dependent variable in our study is ACCEPT, a dummy variable which takes on the value of "1" if the applicant is granted a loan and "0" if denied credit.

Other individual variables derived from the HMDA data used in our model as independent variables include continuous variables for the applicant's income (APNINC), the amount of the loan requested (APNLOAN) and to test for non-linear effects, the square of the applicant's income (SQAPNINC) and the square of the the loan amount requested (SQAPLOAN). We also employ a dummy loan constraint variable (LOANCON3) which estimates the ratio of mortgage payments to income. Since mortgage rates averaged approximately 10% in 1990 (Wefa Group 1990), with a 33% loan payment-to-income ratio, we constrain LOANCON3 to take on the value of "1" if the requested loan amount exceeds 10/3 of the applicant's income and "0" if it does not. Dummy variables are also included to indicate whether the applicant is black (APBLACK), Hispanic (APSPAN), or male (APMALE).

Neighborhood risk variables are derived from the 1990 Census of Population and Housing (File STF-3). The unit of observation for all neighborhood variables is the census tract in Boston and Philadelphia. The variables are the median household income (MEDHHINC), median house value (MEDVALUE), median age of houses (MEDAGSTR), the percent of vacant housing units (RVACUNIT), the percent of owner-occupied units (ROWN) and the percent of households receiving public assistance income (RWELFARE). We also construct a variable to proxy for the risk of real estate investment in the census tract (RENTVAL). RENTVAL is a continuous variable equal to the median rent divided by the median house value.

Finally, we include two variables to represent the proportion of black and Hispanic households in the census tract: RBLACK represents the percent of all households that are headed by a black person; RSPAN is the percent of all households that are headed by an Hispanic individual.

Tables 3 and 4 provide sample statistics for Philadelphia and Boston. As indicated by the neighborhood risk variables, the housing markets in these two cities are quite different. In particular housing is far more expensive in Boston and the homeownership rate is substantially lower with respect to applicants in the sample. Applicant incomes are also higher on average in Boston. Our constructed variables, RENTVAL and LOANCON3, also significantly differ, indicating respectively that the expected rental appreciation rate is higher for the Boston neighborhoods in which our sample is applying for loans and that a higher percentage of applicants are income constrained in that city.

Compared to home purchase mortgages, loan amounts and applicant incomes for home improvement loans in both cities are lower.[14] Within Philadelphia, applicants for refinance loans have higher incomes, larger loan amounts and neighborhood characteristics indicative of somewhat lower risk than applicants for home purchase loans. The reverse pattern holds for Boston.

We examine correlation coefficients for our variables and find that two of our independent variables are relatively highly correlated with RBLACK: APBLACK and RWELFARE.[15] For the sample of home purchase applications, the correlation coefficients between RBLACK and APBLACK in Philadelphia and Boston are .69 and .57, respectively. The correlation coefficients between RBLACK and RWELFARE in the two cities are .51 and .70.

Table 5 shows rates of acceptance by loan type and city. For home purchase loan applicants, the overall acceptance rate in Boston is 75 percent and 85 percent in Philadelphia. These differences in approval rates may be attributable to dissimilar housing market dynamics in the two cities. For both cities, as shown in Table 5, substantial disparities exist in acceptance rates between applicants for loans in census tracts with high proportions of black households and those with low proportions. In Part IV, we examine the sources of these disparities.

IV. Empirical Analysis

In this section, we present the results of estimating the accept/reject models described in Part II. Model 1 contains individual borrower characteristics as explanatory variables. Model 2 adds to these characteristics variables that proxy for neighborhood risk. Each model is estimated separately for Philadelphia and Boston and for each of the types of conventional loans reported by HMDA (ie. home purchase, home improvement and refinancing).[16]

Table 6 presents the estimates of Models 1 and 2 for home purchase loan applicants.[17] The coefficients for RBLACK in Model 1 for both Philadelphia and Boston are negative and significant, results that are consistent with a hypothesis of redlining. When the neighborhood risk variables are added in Model 2, however, we are unable to find a significant relationship between lending decisions and neighborhood racial or ethnic composition.[18]

In the Philadelphia home purchase equations, other independent variables with the exception of MEDVALUE and ROWN (which are not significant) enter both models with the anticipated signs. In Models 1 and 2, the coefficients for both LOANCON3 and APNLOAN are significant. In Boston, in both models the LOANCON3 coefficients are significant and negative as anticipated. The coefficient for APNLOAN in both models has a negative sign, but is not significant. In the two cities, different neighborhood risk variables are significant: in Philadelphia, RVACUNIT and RWELFARE and, in Boston, MEDVALUE and ROWN. In addition, the coefficients for APBLACK and APSPAN in both models in Philadelphia and Boston are negative and statistically significant. We cannot, however, interpret the significance of these variables as indicating the presence of discrimination based upon the race or ethnicity of the applicant. Since we lack individual borrower characteristics, APBLACK and APSPAN are likely to proxy for these missing variables.

Tables 7 and 8 present the results for home improvement and refinance loans. Consistent with the results for home purchase loan applicants, the coefficient for RBLACK in Model 1 is negative and statistically significant in three of the four estimated equations. The exception is for refinancing loans in Philadelphia, where the coefficient is insignificant. In addition, in three of the four estimates of Model 2, the coefficient for RBLACK is statistically insignificant. In one estimation for refinance loans in Boston, we find that the RBLACK coefficient is negative and statistically significant.[19]

The Boston refinance results differ from those in Philadelphia in other ways as well. The coefficients for APNLOAN and RENTVAL are significant and have negative signs in Boston, but not in Philadelphia whereas the LOANCON3 coefficient is significant and negative in Philadelphia, but not in Boston. Moreover, the RVACUNIT coefficient has a positive sign and is statistically significant in the refinance loan equation for Boston. For home improvement loans, all variables in both models perform similarly in Boston and Philadelphia, with both APNINC and APNLOAN coefficients significant with expected signs.

The results also presented in Tables 6, 7 and 8 for the proportion of Hispanic households in each tract are generally consistent with the results for black households. With respect to home purchase loans, the coefficient for RSPAN in Model 1 is negative and significant in both cities. When neighborhood risk variables are entered in Model 2 the coefficient is no longer statistically significant.[20]

The findings for Boston and Philadelphia indicate that when the independent explanatory variables included in our model are restricted to the individual characteristics of the applicant and the size of the loan requested, financial institutions appear to be arbitrarily denying credit to home buyers in minority neighborhoods. Nevertheless, once the set of independent variables is expanded to include measures that proxy for neighborhood risk, the results do not reveal a pattern of redlining. With one exception, our results show similar patterns with respect to applications for home improvement and refinance loans.[21]

Our results suggest that the choice between an Aggregate Study or an Accept/Reject Study may influence the results with respect to a finding of redlining. Our Accept/Reject study fails to support the hypothesis that financial institutions deny credit arbitrarily to black neighborhoods, whereas an Aggregate Study in one of the same cities (Bradbury et al. 1987) found results that supported a conclusion of redlining.[22]

Our study also demonstrates that the omission of proxies for neighborhood risk affects whether disparate racial and ethnic geographic lending patterns are found to exist. Inferring redlining solely from the individual variables contained in the HMDA disclosure reports can be misleading. Although the inclusion of neighborhood risk variables is necessary, the choice of which variables to include is problematic. Insufficient data exist to identify conditions that predict neighborhood decline. Moreover, two of our independent variables are correlated with the proportion of minority households in these areas. In particular, APBLACK and RBLACK have correlation coefficients of

.57 and .69 in Boston and Philadelphia, respectively. Recent studies demonstrate that blacks in both cities live in segregated environments (Massey & Denton 1993). Therefore with the existence of racial segregation in these markets, discrimination against black loan applicants might have a similar effect as redlining black areas. If individual applicant characteristics or neighborhood risk proxies are highly correlated with the proportion of minority households in a neighborhood, including these variables in an Accept/Reject model may generate a finding of no redlining when redlining exists. Similarly, we find that neighborhood risk proxies are significant, but neighborhood racial concentration is not. If neighborhood risk proxies are correlated with neighborhood race and these neighborhood risk proxies do not really affect profitability, then use of these factors in the loan decision would be tantamount to redlining.

Conclusion

In response to recent newspaper articles and academic research showing racial disparities in the home loan mortgage market, policymakers and neighborhood activists have called upon the federal government to increase enforcement of anti-redlining regulations such as the Community Reinvestment Act. Unfortunately, little empirical evidence exists to demonstrate whether financial institutions deny credit systematically to minority communities. Data recently released pursuant to the

Home Mortgage Disclosure Act permit us to examine lending patterns using a methodology that had heretofore not been possible. Rather than test a reduced form equation that confounds the effects of supply and demand, we estimate whether neighborhood racial and ethnic composition affects lenders' decisions to accept or reject loan applications.

Our results do not support the hypothesis that financial institutions redline neighborhoods. Nevertheless, we cannot state definitively that neighborhood racial and ethnic composition is unrelated to lenders' decisions to accept or reject loan applications since HMDA data do not include a full set of individual risk characteristics and those that are included may be correlated with neighborhood risk variables. Our findings, however, should demonstrate the need for further research in this area and caution policymakers against new interventions in the home loan mortgage market that may not be necessary or desirable.

Endnotes

1.Wachter and Megbolugbe (1992) find that differences in group economic endowments explain approximately 80 percent of the difference in the predicted probability of ownership between black and white households.

2.Redlining takes its name from the practice by the Federal Housing Administration of delineating certain areas of cities in which it would not insure loans. These areas were typically those disproportionately composed of racial minorities or neighborhoods in transition (Guttentag & Wachter 1980, Jackson 1985, Wachter 1980).

3.Hula (1992) has been criticized for combining neighborhoods throughout the nation and thereby subjecting his results to biases caused by aggregating disparate samples. See Galster (1992a).

4.The description of discrimination used in this paper does not necessarily track the legal definition of racial discrimination. In some contexts, the failure to grant a loan to an applicant even when the loan's NPV is positive, would not violate the law unless some evidence of an intent to discriminate based upon race is present (Metropolitan Housing Development Corp. v. Village of Arlington Heights 1977).

5.In a broader framework, mortgage terms woiuld be endogenously determined as part of a structural model. Using a single equation approach to model the loan decision may give rise to additional sources of endogeneity. The decision to apply for a loan from a specific lender is likely to be affected by the probablility that the loan application will be accepted. Also, it is possible that lenders who redline some areas might, nonetheless, provide financing for prospective minority home owners in other areas with heavy concentrations of minority households. If so, minority households might be more likely to apply for mortgage loans in these areas. Our model will fail to discern evidence of redlining when such a sorting mechanism occurs. In general the steps a prospective home owner takes between seeking a mortgage loan and actually applying to a specific lender are not well understood. The use of structural equations to model these steps is beyond the scope of this paper.

6.If loan-to-value ratios at the time of loan origination are correlated with areas having higher proportions of minority applicants, our failure to include this variable might bias our results toward finding evidence of redlining when it does not exist. In addition, loan-to-value ratios at the time of loan origination might be higher in neighborhoods with higher proportions of nonwhite households because these households are likely to have less financial assets to use as downpayments

(Wachter and Weicher 1989). This bias toward finding redlining would not exist if other included variables proxy for high loan-to-value ratios.

7.See Rothenberg, Galster, Butler & Pitkin (1991) for a discussion of the theory and empirical evidence on housing investment decisions.

8.On the other hand, if land values are increasing, older houses may become more desirable for redevelopment. If so, a homeowner might disinvest because his rate of return on home repair would be low given that the structure will soon be demolished (Rosenthal & Helsey forthcoming).

9.For a discussion of other reasons why owner-occupied housing is better maintained than investor-owned housing see Galster (1987).

10. High levels of vacant housing may reflect abandonment. Vacant housing may also indicate units for which operating costs exceed market rents. The excess of operating costs over market rents may be attributable to low demand. In addition to vacancies, low demand for housing in a neighborhood is likely to result in low house values. Low median house values may also signal the existence of homes for which it does not pay to make major capital investments.

11.It is also possible, however, that vacant units may reflect speculative investments rather than abandonment.

12.It would be preferable to use the hedonic predicted rent and value for each tract. Unfortunately, the STF-3 Census File used in this study does not contain micro-data that would permit us to compute these estimates.

13.Due to small sample sizes, we were able to estimate only one equation for loans insured by the Federal Housing Administration (FHA). The results of this equation are described in note 16.

14.This disparity may occur because low income households are more likely to purchase homes that are in need of repair.

15.A copy of the correlation matrix is available from the authors.

16.Because of small sample sizes, we could estimate only one equation for FHA-insured loans. Among applicants for FHA-insured home purchase loans in Philadelphia, the coefficient for RBLACK in Model 1 is negative and statistically significant; the estimate for Model 2 is insignificant. Thus the FHA loan estimates, at least with respect to home purchase loans in Philadelphia, are consistent with our results for conventional loans.

Table 1

Summary of Studies on Racial and Ethnic Geographic Disparities in Home Loan Mortgage Markets

Author	Data	Methodology	Geographic Scope	Dependent Variable(s)	Measure(s) of Geographic Racial and Ethnic Disparity	Selected Control Variables
Ahlbrandt (1977)	Census tract data (1970) Pittsburgh City Planning Department data (1973-1974)	Aggregate	Pittsburgh	Aggregate value of mortgage loans, aggregate number of mortgage loans in Census tracts	Percent of population black, Change in percent of black population in Census tracts	Median family income (+), percent of owner occupied housing, percent of vacant units (-), crime rate
Avery and Buynak (1981)	HMDA (1977-1979), Census tract data (1970)	Aggregate	Cleveland	Ratio of aggregate number of bank and S&L loans in Census tracts to aggregate number of deed transfers in Census tracts	Change in percentage black 1970-1977 in Census tracts (- -)	Median income, median value, percent change in value, percent of housing in place before 1939, percent below poverty level, percent professional (+), percent owner occupied, percent foreclosure actions per owner occupied house
Bradbury,Case,Dunham(1989)	Deed transfer data, Census tract data (1980)	Aggregate	Boston	Aggregate number of loans originated from 1982 to 1987 per 100 separately owned structures and condominium units in Boston's 64 NSAs (Census tract groupings)	Percent minority other than black and percent black (-) in NSAs	Median NSA income (-), wealth (+), home value (-), rent (+), vacancy rate (-), % of properties which are commercial or industrial, mobility rate (+), age (+)
Canner and Smith (1991)	HMDA (1990), Census tract data (1990)	Accept/Reject	United States	Proportion of loan applications rejected in Census tracts	Percent of minorities in Census tracts *	*
Canner and Smith (1992)	HMDA (1991), Census tract data (1990)	Accept/Reject	United States	Proportion of loan applications rejected in Census tracts	Percent of minorities in Census tracts *	*
Hula (1992)	HMDA data (1981-87) and Census tract data (1980)	Aggregate	United States	Standardized measures of the aggregate dollar value and aggregate number of conventional, FHA/VA, and home improvement loans in Census tracts	Percent minority in Census tracts (+ + - -)	Number of owners(+), total housing units, recently constructed housing units, population, average income, SMSA income, located in central city
Hutchinson,Ostas,Reed(1977)	Census tract data (1970), HMDA data (1975)	Aggregate	Toledo, OH	Aggregate number of loans, conventional loans, and home-improvement loans in Census tracts	Percent of population black (+ + - -) percent of population black squared (+ +), change in percent black 1960-1970 in Census tracts	Average age of residential structures, unemployment rate, median years of education (+), median income, number of owner-occupied dwellings(+),median property value, change in property value 1960-1970, percent population over 55, average duration of residency, percent of population having moved into census tract in the last two years, persons per household(+)
Listokin and Casey (1980)	Census data (1970), Federal Home Loan Bank Board Survey of 189 Cook County S&Ls (1971-1973) aggregated by zip code	Aggregate	Cook County, IL	Aggregate number of mortgages granted per 1000 households in zip codes	Percent white (+) in zip codes	% owner occupied houses, % of vacant units, median age of housing, median value owner-occupied house, median family income, applicant is male (+), applicant is female, applicant is married(+), single,divorced, widowed,income(+),years of employment (+), spouse's years of employment, low debt (+), applicant's monthly debt payments (-), applicant's assets (+), amount of requested loan(-), purchase price of property (+)
Munnell, Browne, McEneaney Tootell (1992)	HMDA (1990), Census tract data (1990)	Accept/Reject	Boston	Probability an applicant was denied a mortgage loan	Percent black greater than 30% in Census tracts	Housing expense/income(+), total debt/income(+), net wealth, consumer credit history (+), mortgage credit history (+), public record history (+), probability of unemployment (+), self employed (+), loan/appraised value(+), denied private mortgage insurance (+), rent value in tract(+), purchasing 2-4 family home(+)

Table 1--Continued

Summary of Studies on Racial and Ethnic Geographic Disparities in Home Loan Mortgage Markets--Continued

Author	Data	Methodology	Geographic Scope	Dependent Variable(s)	Measure(s) of Geographic Racial and Ethnic Disparity	Selected Control Variables
Schafer (1978)	Census tract data (1970), NY state regulated lenders in 1975	Aggregate	Buffalo, New York and Nassau-Suffolk, Syracuse, Rochester, and Albany-Troy-Schenectady	Quantity of conventional and federally insured mortgages on one to four family houses as well as multifamily houses in Bronx, Kings, and Queens counties in Census tracts	Percent of 1974 population which is nonwhite (- -), change in percent of nonwhite population 1970-1974 in Census tracts(- - + +)	Value per building(+), fraction units vacant 1969, change in fraction vacant 1969-1975, tax arreage on 1-4 family unit buildings, change in tax arrearage on 1-4 unit buildings, change in per capita income, per capita welfare, change in per capita welfare, change in population, ratio of foreclosures to total loans, fraction of buildings built before 1939, % of households earning above $15,000, average property value, tax arreage on 1-4 family unit buildings, change in tax arrearage on 1-4 unit buildings,
Schafer and Ladd (1981)	HMDA (1976-1978), Census tract data (1970), IRS data (1976) aggregated by zip code	Accept/Reject	Several major metropolitan areas in the states of California and New York	Proportion of loan applicants rejected in Census tracts	Percent black(- -), Hispanic Ca. only)(- -), Asian(Ca. only) (+) in Census tracts	Loan/income(+), loan/appraised value(+), fraction of households earned above 15000 in 1969 (-),median 1976 income (-), decreases in mean income last year (+), houses built before 1940 (+)
	HMDA (1976-1978), Census tract data (1970), IRS data (1976)	Aggregate	Kings, Queens, and Bronx counties in New York	Quantity of convential mortgages on 1 to 4 family houses in Kings, Queens, and Bronx counties on a per building basis in Census tracts	Percent nonwhite (- -), change in percent nonwhite 1970-1974(- -)	1-to-4 family buildings ($ per building) (+), stock of conventional multifamily mortgages ($ per building), fraction of 1-to-4 unit buildings vacant 1969, tax arreage on 1-to-4 unit buildings, 1972 (fraction of buildings 3/4 or more in arrears), per capita welfare 1970, fraction of 1-to-4-unit buildings built in 1939 or earlier
Shlay (1988)	Census tract data (1980), HMDA (1980-1983)	Aggregate	Chicago	Log of the aggregate number and quantity of conventional single family loans made by commercial banks, S&Ls and FHA loans made by mortgage bankers in Census tracts	Percent black (-)and percent Hispanic (- -) in Census tracts	Median household income(+), percent married couples with children, percent population in different house in 1975(+), median value of owner-occupied house, number of 1-4 unit structures and condominiums(+),% owner occupied, % condominiums,% built 1975-1980,% built before 1940,% units vacant for sale, Lakefront(+)
Shlay (1989)	Census tract data (1980), HMDA data (1981-1984)	Aggregate	Baltimore	Log of the aggregate number and quantity of conventional single family loans made by commercial banks, S&Ls and FHA loans made by mortgage bankers in Census tracts	Percent black (-) in Census tracts	Gentrification dummy(+), median household income, % single(-), % population in different house in 1975, median value owner occupied house(+), number of 1-4 unit structures/condominiums(+), % owner-occupied, % condominiums, %built 1975-1980, % built before 1940(-), % units vacant for sale

+ indicates a positive and statistically significant relationship between variable and dependent variable in all models tested
+ + indicates for Geographic Racial and Ethnic Disparity variable that relationship between the variable and the dependent variable is sometimes positive and significant
- indicates a negative and statistically significant relationship between variable and dependent variable in all models tested
- - indicates for Geographic Racial and Ethnic Disparity variable that relationship between the variable and the dependent variable is sometimes negative and significant
*The analysis in Canner and Smith(1992)is limited to crosstabulations. A positive relationship exists between the proportion of minorities in a census tract and whether a loan application is rejected. No tests of statistical significance were conducted.

TABLE 2: Definition of Variables	
Variable Name	Variable Definition
ACCEPT	1 if loan application is approved; 0 if denied
LOANCON3	1 if loan amount requested is greater than 10/3 of applicant's income; 0 if not
APNINC	Applicant's income (in $1,000's)
SQAPINC	Square of APINC divided by 10,000
APNLOAN	Amount of loan requested (in $1,000's)
SQAPLOAN	Square of APNLOAN divided by 100,000
APBLACK	1 if race of applicant is black; 0 if not
APSPAN	1 if ethnicity of applicant is Hispanic; 0 if not
APMALE	1 if sex of applicant is male; 0 if not
MEDHHINC	Median household income in census tract
MEDVALUE	Median house value in census tract
MEDAGSTR	Median age of houses in census tract
ROWN	Percent of owner-occupied housing units in census tract
RVACUNIT	Percent of vacant housing units in census tract
RENTVAL	Median rent divided by MEDVALUE in census tract
RWELFARE	Percent of households in census tract receiving any public assistance income
HHRSPAN	Percent of households in census tract headed by person whose ethnicity is Hispanic
HHRBLACK	Percent of households in ceneus tract headed by person whose race is black

TABLE 3: Sample Statistics for Philadelphia
A. Home Purchase Loans

	All Applications		Rejected Applications		Accepted Applications	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
ACCEPT	0.845					
LOANCON3	0.01	0.12	0.04	0.21	0.01	0.09
APNINC	45.3	122.7	44.7	298.6	45.4	38.7
SQAPNINC	1.7	100.6	9.1	255.7	0.4	1.7
APNLOAN	59	50	45	44	61	51
SQAPLOAN	0.06	0.27	0.04	0.14	0.06	0.29
APBLACK	0.19	0.40	0.41	0.49	0.15	0.36
APSPAN	0.07	0.25	0.09	0.29	0.06	0.24
APMALE	0.72	0.45	0.64	0.48	0.73	0.44
MEDHHINC	28019	9512	24386	8972	28684	9458
MEDVALUE	70535	50340	52986	44611	73746	50670
MEDAGSTR	42.7	11.1	45.9	9.3	42.1	11.3
ROWN	68.0	17.2	66.5	15.9	68.2	17.5
RVACUNIT	8.5	5.5	10.4	6.0	8.1	5.3
RENTVAL	0.73	0.36	0.90	0.39	0.70	0.34
RWELFARE	10.5	10.0	15.3	11.8	9.6	9.4
RSPAN	4.7	11.3	6.3	14.6	4.4	10.6
RBLACK	21.8	33.8	39.1	41.1	18.6	31.2
N =	5334		825		4509	

TABLE 3: Sample Statistics for Philadelphia (cont.)
B. <u>Home Improvement Loans</u>

	All Applications		Rejected Applications		Accepted Applications	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
ACCEPT	0.668					
LOANCON3	0.01	0.10	0.02	0.13	0.01	0.09
APNINC	34.3	78.1	31.4	130.1	35.7	26.8
SQAPNIC	0.7	28.9	1.8	50.2	0.2	0.7
APNLOAN	10	17	11	21	10	15
SQAPLOAN	0.00	0.09	0.01	0.15	0.00	0.02
APBLACK	0.30	0.46	0.40	0.49	0.25	0.43
APSPAN	0.07	0.25	0.09	0.29	0.05	0.22
APMALE	0.68	0.47	0.62	0.49	0.71	0.45
MEDHHINC	25974	9287	23568	8181	27169	9569
MEDVALUE	55313	38532	45419	30646	60225	41027
MEDAGSTR	45.2	9.6	47.1	8.0	44.2	10.1
ROWN	69.1	15.3	67.5	15.1	69.9	15.4
RVACUNIT	9.2	5.8	10.4	6.0	8.6	5.5
RENTVALx100	0.84	0.37	0.95	0.39	0.79	0.35
RWELFARE	13.5	11.4	16.5	12.4	12.0	10.6
RSPAN	5.1	13.2	6.9	15.6	4.3	11.7
RBLACK	33.1	40.3	41.9	41.3	28.7	39.0
N =	5531		1835		3696	

TABLE 3: Sample Statistics for Philadelphia (cont.)

C. <u>Mortgage Refinance Loans</u>

	All Applications		Rejected Applications		Accepted Applications	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
ACCEPT	0.808					
LOANCON3	0.02	0.13	0.04	0.19	0.01	0.11
APNINC	58.6	73.0	50.7	51.3	60.4	77.2
SQAPNINC	0.9	6.5	0.5	1.8	1.0	7.2
APNLOAN	68	64	65	56	69	65
SQAPLOAN	0.09	0.29	0.07	0.18	0.09	0.31
APBLACK	0.13	0.33	0.22	0.41	0.11	0.31
APSPAN	0.03	0.16	0.04	0.20	0.02	0.15
APMALE	0.78	0.42	0.74	0.44	0.79	0.41
MEDHHINC	30273	9130	28961	8358	30584	9281
MEDVALUE	80763	50164	74832	45222	82171	51189
MEDAGSTR	42.4	10.8	43.6	10.3	42.1	10.9
ROWN	67.4	17.9	65.6	18.9	67.9	17.6
RVACUNIT	8.0	5.7	8.7	5.2	7.8	5.7
RENTVALx100	0.63	0.30	0.68	0.35	0.62	0.29
RWELFARE	7.9	7.2	9.1	7.8	7.6	7.0
RSPAN	2.5	5.8	3.0	7.6	2.4	5.2
RBLACK	18.3	30.3	24.7	34.2	16.8	29.2
N =	1204		231		973	

TABLE 4: Sample Statistics for Boston
A. Home Purchase Loans

	All Applications		Rejected Applications		Accepted Applications	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
ACCEPT	0.751					
LOANCON3	0.16	0.36	0.29	0.45	0.12	0.32
APNINC	71.1	81.6	63.0	91.1	73.8	78.1
SQAPNINC	1.2	8.2	1.2	13.8	1.2	5.0
APNLOAN	137	90	143	105	135	85
SQAPLOAN	0.27	0.75	0.31	1.14	0.25	0.56
APBLACK	0.22	0.42	0.41	0.49	0.16	0.37
APSPAN	0.05	0.23	0.07	0.26	0.05	0.22
APMALE	0.73	0.44	0.74	0.44	0.73	0.45
MEDHHINC	33000	9050	30464	9029	33841	8901
MEDVALUE	218834	122489	195040	108019	226723	125967
MEDAGSTR	46.5	8.9	46.5	8.8	46.5	9.0
ROWN	33.6	15.6	31.1	14.1	34.5	16.0
RVACUNIT	8.7	4.5	9.2	4.9	8.6	4.3
RENTVAL	0.36	0.13	0.37	0.12	0.35	0.13
RWELFARE	10.6	8.7	14.0	10.2	9.6	7.8
RSPAN	7.0	7.7	9.2	9.1	6.2	7.0
RBLACK	21.5	31.1	33.3	36.1	17.5	28.2
N =	1996		497		1499	

TABLE 4: Sample Statistics for Boston (cont.)

B. <u>Home Improvement Loans</u>

	All Applications		Rejected Applications		Accepted Applications	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
ACCEPT	0.821					
LOANCON3	0.01	0.12	0.03	0.16	0.01	0.11
APNINC	55.2	63.4	45.7	33.6	57.3	68.0
SQAPNINC	0.7	5.2	0.3	0.8	0.8	5.7
APNLOAN	33	77	30	47	34	82
SQAPLOAN	0.07	0.59	0.03	0.13	0.08	0.65
APBLACK	0.27	0.45	0.43	0.50	0.24	0.43
APSPAN	0.06	0.23	0.10	0.31	0.05	0.21
APMALE	0.71	0.46	0.64	0.48	0.72	0.45
MEDHHINC	31615	7707	29714	7836	32031	7623
MEDVALUE	168939	63644	154819	48406	172026	66150
MEDAGSTR	47.7	6.6	47.3	6.8	47.8	6.6
ROWN	34.8	13.5	31.9	12.7	35.4	13.6
RVACUNIT	8.0	3.6	8.7	3.7	7.8	3.6
RENTVALx100	0.40	0.10	0.42	0.11	0.40	0.10
RWELFARE	13.3	8.8	16.8	9.7	12.6	8.4
RSPAN	7.9	7.9	9.2	7.2	7.7	8.0
RBLACK	34.7	37.8	50.6	38.2	31.2	36.8
N =	641		115		526	

TABLE 4: Sample Statistics for Boston (cont.)
C. Mortgage Refinance Loans

	All Applications		Rejected Applications		Accepted Applications	
	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
ACCEPT	0.747					
LOANCON3	0.11	0.32	0.18	0.38	0.09	0.29
APNINC	69.9	64.0	69.5	51.8	70.0	67.6
SQAPNINC	0.9	3.0	0.8	2.1	1.0	3.3
APNLOAN	126	102	151	121	118	93
SQAPLOAN	0.26	0.80	0.37	1.23	0.23	0.59
APBLACK	0.16	0.37	0.29	0.45	0.12	0.32
APSPAN	0.03	0.17	0.05	0.22	0.02	0.14
APMALE	0.74	0.44	0.71	0.45	0.75	0.43
MEDHHINC	32594	8683	30832	8845	33190	8550
MEDVALUE	198342	103754	196327	105983	199024	103040
MEDAGSTR	47.5	7.5	46.7	8.7	47.8	7.1
ROWN	34.4	14.9	30.2	12.6	35.8	15.4
RVACUNIT	8.2	4.1	8.6	3.5	8.1	4.3
RENTVALx100	0.37	0.11	0.38	0.12	0.37	0.11
RWELFARE	11.3	8.6	13.8	9.7	10.4	8.1
RSPAN	6.8	7.3	8.8	7.9	6.2	7.0
RBLACK	22.0	32.8	35.3	37.9	17.5	29.6
N =	1203		304		899	

TABLE 5: Accept Rates by Census Tract Racial and Ethnic Composition

City and Loan Type	Percentage Accepted in All Tracts	Percentage Accepted in Nonhispanic Tracts	Percentage Accepted in Hispanic Tracts	Percentage Accepted in Nonblack Tracts	Percentage Accepted in black Tracts
Philadelphia					
Home Purchase	84.5	85.1	81.2	88.2	71.9
Home Improvement	66.8	68.7	53.9	72.1	57.2
Mortgage Refinance	80.8	90.0	78.8	82.5	73.8
Boston					
Home Purchase	75.1	79.5	65.5	81.1	59.3
Home Improvement	82.1	86.7	74.7	88.9	73.7
Mortgage Refinance	74.7	79.7	63.9	80.9	58.4

Notes:

Hispanic tracts are defined as those census tracts whose proportion of Hispanic households is at or above the city-wide average. The average percentage of total households that are Hispanic is 4.65 and 7.08 for Philadelphia and Boston, respectively. Black tracts are defined as those census tracts whose proportion of black households is at or above the city-wide average. The average percentage of total households that are black is 36.4 and 19.3 for Philadelphia and Boston respectively. All differences between nonminority and minority census tracts are statistically significant at the 99 percent confidence level.

TABLE 6: Home Purchase Loan Applications

	Philadelphia		Boston	
	Model 1	Model 2	Model 1	Model 2
LOANCON3	-0.2720**	-0.2713**	-0.1223**	-0.1170**
APNINC	0.00018	0.00009	0.00059*	0.00057*
SQAPNINC	-0.00292	-0.00096	-0.00443	-0.00439
APNLOAN	0.00094**	0.00067**	-0.00034	-0.00040
SQAPNLOAN	-0.06487**	-0.03932	-0.00602	-0.00324
APBLACK	-0.11451**	-0.11683**	-0.17830**	-0.19276**
APSPAN	-0.06361**	-0.05974**	-0.08776**	-0.10277**
APMALE	0.00124	-0.00015	-0.04394*	-0.04439*
MEDHHINC		2.10E-06		-1.65E-06
MEDVALUE		-3.41E-07		4.56E-07*
MEDAGSTR		-0.00050		-0.00057
ROWN		-0.00049		0.00280*
RVACANT		-0.00229*		-0.00129
RENTVAL		-2.43		25.71
RWELFARE		-0.00210**		0.00015
RSPAN	-0.00086*	0.00077	-0.00402**	-0.00206
RBLACK	-0.00084**	-0.00029	-0.00088**	-0.00056
Intercept	1.826	2.443	2.041	0.960
N	5334	5334	1996	1996
-2Ln(L)	4182.0	4148.2	2036.3	2023.6
Chi-sq	413.0	446.8	204.1	216.8

Notes:

The dependent variable in each logit is a binary indicator of whether or not the loan application was accepted (1) or rejected (0). The number given for each independent variable is the partial derivative of the expected probability that a loan application is accepted with respect to the given variable, evaluated at the sample means of all the variables.

*:= significant at the .10 level (two-tailed test).

**:= significant at the .05 level (two-tailed test).

TABLE 7: Home Improvement Loan Applications

	Philadelphia		Boston	
	Model 1	Model 2	Model 1	Model 2
LOANCON3	0.07627	0.07543	-0.05912	-0.05648
APNINC	0.00703**	0.00639**	0.00222**	0.00209**
SQAPNINC	-0.16511**	-0.15917**	-0.02979*	-0.02795
APNLOAN	-0.00441**	-0.00492**	-0.00111*	-0.00124*
SQAPNLOAN	0.50957**	0.56613**	0.21784	0.20019
APBLACK	-0.11033**	-0.11357**	-0.09038**	-0.08829**
APSPAN	-0.09465**	-0.10002**	-0.16495**	-0.16242**
APMALE	0.01965	0.02349	0.02375	0.03102
MEDHHINC		1.25E-06		-4.41E-06
MEDVALUE		1.26E-06**		5.78E-07
MEDAGSTR		-0.00092		0.00107
ROWN		0.00107		0.00319
RVACANT		-0.00110		0.00068
RENTVAL		-4.061		-14.975
RWELFARE		0.00095		-0.00573
RSPAN	-0.00206**	-0.00045	0.00044	0.00326
RBLACK	-0.00058**	0.00023	-0.00125**	-0.00033
Intercept	0.313	-0.187	1.528	1.408
N	5531	5531	641	641
-2Ln(L)	6560.5	6498.2	559.7	552.6
Chi-sq	468.6	530.8	43.5	50.6

Notes:

The dependent variable in each logit is a binary indicator of whether or not the loan application was accepted (1) or rejected (0). The number given for each independent variable is the partial derivative of the expected probability that a loan application is accepted with respect to the given variable, evaluated at the sample means of all the variables.

*:= significant at the .10 level (two-tailed test).
**:= significant at the .05 level (two-tailed test).

TABLE 8: Mortgage Refinance Loan Applications

	Philadelphia		Boston	
	Model 1	Model 2	Model 1	Model 2
LOANCON3	-0.15600**	-0.15549**	-0.04035	-0.03833
APNINC	0.00078	0.00067	-0.00077	-0.00064
SQAPNINC	-0.00458	-0.00375	0.04700	0.04662
APNLOAN	-0.00064	-0.00072	-0.00127**	-0.00125**
SQAPNLOAN	0.07440	0.08169	0.04060	0.03122
APBLACK	-0.12628**	-0.14508**	-0.10523**	-0.11725**
APSPAN	-0.11520	-0.12926*	-0.11270	-0.12205*
APMALE	0.02316	0.02333	0.04781	0.04502
MEDHHINC		-9.59E-07		-3.78E-06
MEDVALUE		4.33E-07		-2.80E-07
MEDAGSTR		-0.00063		0.00223
ROWN		0.00144		0.00582**
RVACANT		-0.00003		0.00712*
RENTVAL		-3.37		-58.53**
RWELFARE		-0.00127		-0.00052
RSPAN	-0.00092	0.00099	-0.00508**	-0.00363*
RBLACK	-0.00015	0.00056	-0.00174**	-0.00142**
Intercept	1.515	1.205	2.412	2.465
N	1204	1204	1203	1203
-2Ln(L)	1143.1	1137.7	1229.4	1205.0
Chi-sq	34.1	39.6	130.7	155.0

Notes:

The dependent variable in each logit is a binary indicator of whether or not the loan application was accepted (1) or rejected (0). The number given for each independent variable is the partial derivative of the expected probability that a loan application is accepted with respect to the given variable, evaluated at the sample means of all the variables.

*:= significant at the .10 level (two-tailed test).

**:= significant at the .05 level (two-tailed test).

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