RACE, INCOME, AND THE APPROVAL OF HOME MORTGAGES: AN ANALYSIS USING AGGREGATED DATA

Esther Y. Gesick and Donald N. Steinnes*

Introduction

National attention recently has focused on allegations of racial discrimination in home mortgage lending by banks and thrifts.[1] These allegations have been spawned by a study by the Board of Governors of the Federal Reserve System (1991) that summarizes borrower characteristics from data collected pursuant to the revised Home Mortgage Disclosure Act.[2] While the Board's study is cautious about drawing the conclusion that differentials between rejection rates for mortgages between whites and nonwhites are due to discrimination, the study did indicate that the rejection rates for blacks, Hispanics, and American Indians are substantially above those for whites and Asian-Americans. Moreover, applicants trying to purchase homes in low or moderate income neighborhoods are rejected more frequently than those wishing to purchase homes in higher income neighborhoods, which may indicate the continuing practice of redlining by banks and thrifts.[3] The study did control for income. It did not, however, take into account individual applicants' asset levels, debt burdens, employment histories, and credit histories, nor did the study take into account whether the property an applicant was seeking to purchase is valued adequately. Such data are not currently available, as the lending institutions are not required to report such information.

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[1] See, for example, the articles in the *Arizona Republic* (1991) and the *Wall Street Journal* (1992).

[2] The Home Mortgage Disclosure Act was amended on June 15, 1989. See discussion of H.R. 1278. The Home Mortgage Disclosure Act was amended on June 15, 1989. See discussion of H.R. 1278.

[3] *Redlining* refers to lenders' practice of refusing mortgage applications to purchase property in a specific geographic neighborhood, usually a low income neighborhood.

The issue of racial discrimination in mortgage lending is not new. It has surfaced several times over the last 20 years. Media attention on the issue in the mid-1970s led to passage of the Home Mortgage Disclosure Act (HMDA) of 1975 and the Community Reinvestment Act (CRA) of 1977. Both acts were expanded in 1989, again as a response to public criticism that the original versions were not stringent enough.[4] HMDA requires all financial institutions engaged in home mortgage lending to publicly disclose the disposition by race, marital status, gender, and income of all mortgage and home improvement loan applications received. Institutions also must disclose the geographic location (by census tract) in which the property is located and the socioeconomic characteristics of the neighborhood. The CRA obligates banks and thrifts to make a concerted attempt to meet the credit needs of all residents within their communities, both those in upper income areas and those in low and moderate income areas.

Early studies in the 1970s (Black *et al.*, 1978; Hutchinson *et al.* 1977) on racial discrimination in mortgage lending are inconclusive or are unable to detect discrimination except to a limited extent. Studies in the 1980s yield somewhat stronger evidence of discrimination, though these studies are sometimes controversial.

A series run by the *Atlanta Constitution* in 1988 indicates that banks and thrifts issue substantially more home purchase loans per single family housing unit in predominantly white neighborhoods than in predominantly minority neighborhoods. A Federal Reserve Board analysis (1988) of the *Atlanta Constitution* study, however, concludes that the disparity can be explained by other factors, such as higher turnover rates of property in white neighborhoods compared to minority neighborhoods or by lenders' perceptions of default risk of each group of applicants.

Key studies on lending discrimination by Gabriel and Rosenthal (1991) and by Canner, Gabriel, and Woolley (1991) focus on the effect of lenders' perceptions of default risk on the probability of individuals obtaining conventional versus government-backed mortgage loans. The authors conclude that neighborhoods that have a high proportion of minorities are characterized by a high proportion of mortgage loans that are FHA-insured. To a large extent this seems to be explained by lenders' perceptions of default risk.[5] After controlling for default risk,

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[4] See, for example, the series run in the *Atlanta Constitution* (1988) and the *Detroit Free Press* (1988). Also see Yinger (1986).

[5] In the absence of government-guaranteed mortgage loans, borrowers with high default risk would be rationed out of the credit market. Thus, FHA guaranteed loans make it worthwhile for lenders to make loans to borrowers who are less creditworthy. From the borrowers standpoint, however, an FHA loan is more expensive than a conventional loan.

however, the studies still indicate that race effects persist. It could not be determined, however, whether these race effects are due to lender bias or to other factors such as preferences for government-backed mortgages, market specialization of lenders, or steering by real estate agents.

One problem inherent in all of these studies on the issue of mortgage lending discrimination is that data on rejected applicants are not available prior to 1991 because lenders were not required to report such information under HMDA prior to the 1989 amendment. Since 1990 lending institutions have been required to report the characteristics of applicants and of census tracts in which properties for which mortgages are sought for all mortgage loan applications, both those accepted and those rejected. This data set was made available to the public in the fall of 1991. The availability of these new data is likely to yield more information concerning racial discrimination.

The *Wall Street Journal* (1992) recently conducted a study using the new data that examine the disparities in the approval rates for home mortgages for whites and blacks. The analysis is limited to these two racial groups because the disparities in approval rates for blacks and whites appears to be much greater than between other racial or ethnic groups. The results are broken down by state and are given in terms of approval rates for individual lending institutions within each state. In order to be included in the study, a lending institution had to have received at least 50 home mortgage applications from each of the two racial groups. All types of lending institutions are included in the study.

The analysis of the study indicates that rejection rates for blacks are much higher than for whites for virtually all states and most institutions. These disparities exist when the researchers hold income and loan size constant and also in cases when the borrowers' income is large relative to loan size.

The *Wall Street Journal* study only demonstrates that large disparities exist between approval rates on mortgages for blacks and whites. While the authors imply that these results are likely the result of discriminatory practices by the lending institutions, the study does not attempt to test this hypothesis statistically by ruling out other factors that may explain the disparities. Thus, we have chosen to use regression analysis to see to what extent the differences in approval rates can be explained by factors other than race and to what extent discrimination seems to be present. Our study departs from previous statistical studies on discrimination in mortgage lending in that we are conducting our tests using data aggregated by state, with average income for each racial group, characteristics of the housing market, and health of the banking industry considered for each case.

Our data on acceptance rates come from the *Wall Street Journal* article that obtained the information from the disclosures of financial institutions pursuant to the amendment to HMDA. The data are broken down by race and state. In addition, data on the demographic and economic characteristics of states are obtained from the *1980 and 1990 Censuses of Population and Housing*. The data on the health of the banking industry for each state are obtained from a *Wall Street Journal* article (1990) about Resolution Trust Corporation properties held in each state.

Model Specification

In order to test for racial discrimination in the approval of home mortgages it is necessary to have data concerning the disposition of loan applications for a sample. The HMDA data provides this type of information; our intent is to develop models that can use these data to test statistically for the presence of racial discrimination. It is important in proving discrimination using statistical methods to be able to control for other factors influencing loan approval in the model. We intend to do this using multivariate procedures. The information available concerning the applicants is limited, however, so it is not possible to consider all relevant determinants of approval.

The modeling approaches vary based on the nature of the data available. If and when HMDA data are released for individual applications, it would be possible to specify a model with a binary (e.g., 1 if loan approved, 0 if not) dependent variable. Such an approach would use characteristics of the applicant (e.g., income and credit rating) and introduce a binary race variable to test for the presence of racial discrimination. Such an approach has been taken by Munnell *et al.* (1992) for the Boston area, but the HMDA data are supplemented by the collection of additional information. While the results indicate racial discrimination in Boston, this has been challenged by Liebowitz (1993). The questions he raises about the findings center on the accuracy and validity of specific cases and whether these cases are necessary to reach a conclusion of discrimination. This controversy, and the fact the data used in the Boston study are not available for the whole country, has led us to test for discrimination using an aggregated data approach.

We intend to estimate models that have as the dependent variable the loan approval rate of a particular racial group, in a particular state, for a particular bank. This aggregate approach will be analogous to the microdata model previously indicated and will use aggregated independent variables (e.g., average income for a particular racial group in a particular state). By using aggregated independent variables the potential for extreme values influencing the result is reduced. As noted, this has been the major question raised with regard to the Boston study (1992) based on supplemental HMDA microdata.

This sort of aggregated version of a micromodel has a precedent in the migration literature where most studies are done using states as cases and rates as the dependent variable. The independent variables are aggregates such as average income and unemployment rates for the origin and/or destination state. These migration models have been tested for different demographic groups (e.g., race and age) using methods similar to those that will be employed in this paper. The conclusions drawn from such aggregated models generally have been consistent with results obtained from comparable micro models. (See Greenwood (1975) for survey of migration literature.)

In general, we propose a model with the following specification:

$$(1) \quad APPRATE_{ijk} = f(GROUPCHAR_{ij}, STATECHAR_{j}, BANKCHAR_{k})$$

where:

$APPRATE_{ijk}$ = Loan approval rate of racial group i in state j by bank k;
$GROUPCHAR_{ij}$ = Characteristics of racial group i in state j;
$STATECHAR_{j}$ = Characteristics of state j: and
$BANKCHAR_{k}$ = Characteristics of bank k

The intent is to use not only the characteristics of the applicants (GROUPCHAR) but also information pertaining to the state and the bank taking the application. While the currently available HMDA data allow for some specification of each of the three types of characteristics, we do not intend in this paper to consider BANKCHAR for individual banks. We will use a variable (BANKPROB) measuring the conditions of all banks in a particular state, however, which makes it a STATECHAR rather than a BANKCHAR variable. Because the APPRATE data are for 1990, we have attempted to specify all independent variables for the same year, 1990.

The GROUPCHAR variable is a vector of several characteristics for each racial group in each state obtained from the *1990 Censuses of Population and Housing*. In particular, we will use the average income (AVEINC), percentage of home ownership (HOMEOWN), and percentage of population (PERPOP) for each of two racial groups, white and black, for the 50 states and the District of Columbia. It should be noted that results comparable to those that will be presented were obtained when the models were estimated for the 48 contiguous states.

We would hypothesize that higher income levels would increase the probability of loan approval. Our hypothesis for HOMEOWN, the percentage of racial group households that are homeowners, is more ambiguous. If HOMEOWN is high, it may mean that the pool of qualified potential homeowners in the state is low and so approval rates will be low. On the other hand, high HOMEOWN reflects many households with equity and, thus, a higher potential for being approved. While it would be possible to distinguish these two possibilities if applicants could be divided into first-time and not first-time buyers, the data available combine both types of applicants.

In addition, we have included two variables that are the same for each racial group in a particular state j or $STATECHAR_j$. The first is the percentage change in home prices in the state between 1980 and 1990, HOMPRICG. We expect this to have a positive influence on loan approval because it indicates a strong housing market and less risk of default. The final variable is a first attempt to consider what influence bank problems in the state might have on loan approval rates. For this we have what percentage of the housing stock in each state was held by the Resolution Trust Corporation (BANKPROB) in 1990. We expect states with large percentages to have lower approval rates for each racial group. In a later study we will measure problems for individual banks and determine the extent to which such problems influence loan approval rates.

Table 1—Descriptive Statistics (n = 51)

Panel A: Racial Group

Variable:	Mean White (W)	Mean Black (B)	Standard Deviation White (W)	Standard Deviation Black (B)
APPRATE	.867	.696	.038	.103
AVEINC	38,563	25,878	8,100	5,191
HOMEOWN	.682	.398	.065	.103
PERPOP	.828	.104	.139	.122

Panel B: Simple Correlations (White—W vs. Black—B)

	APPRATEW	AVEINCW	HOMEOWNW	PERPOPW
APPRATEB	.599	.229	.242	.073
AVEINCB	.489	.759	.316	-.120
HOMEOWNB	-.324	-.040	-.635	-.352
PERPOPB	-.067	.433	-.456	-.726

Before proceeding to estimation of the models, we will provide some indication of racial differences for the variables to be considered. Table 1 gives means, standard deviations, and simple correlations that show substantial racial differences using the states as sample observations. The difference in mean approval rates (APPRATE) would, by itself, suggest that racial discrimination may be present. To make such a determination requires that other things be controlled in a multivariate model, however. The three race-specific independent variables, AVEINC, HOMEOWN, and PERPOP, show even greater differences for the two racial groups. If one accepts income and home ownership as legitimate criteria for loan approval, then it may be that differences in white/black approval rates reflect the corresponding differences in income and home ownership seen in Table 1. The correlations in Table 1 are between white and black variables. The values on the diagonal show, as expected, that approval rates and incomes correlate positively for the two racial groups.

Estimation Results

In order to estimate the approval rate model, equation (1), we have used linear[6] ordinary least squares procedures. The results for each racial group are provided in columns (1)—white and (2)—black of Table 2. As expected, income is positive and the most significant variable for each group. Home ownership is significantly positive for whites, but insignificant for blacks which suggests that whites are approved more often if they are homeowners. The BANKPROB variable is negative, as hypothesized, for both racial groups, which suggests that approval rates have been affected adversely by bank problems in the state. This variable is not significant in these and subsequent tests, however. The price appreciation variable, HOMEPRICG, and percentage variable, PERPOP, are generally insignificant; therefore, they will not be discussed further. A final comment on the white (model 1) and black (model 2) results in Table 2 is that the overall explanation (R^2) provided is about the same for the two groups. It remains to determine, in Table 3, if the models (i.e., intercepts and slopes) are the same for the two groups.

An alternative model is to use the difference in approval rates (DIFFAPP) as the dependent variable. In column (3) of Table 2 the white and black variables are used, but only the income variable proves to be significant. The signs for the race-specific variables (income, home ownership, and share of population) suggest that using the differences in these variables as independent variables would be viable. Using such differencing (model 5), however, results in a lower R^2 and a less significant F-value. Again, the only significant variable is the one measuring income, and it has the correct (positive) sign.

Another approach using differences is to include one group's approval rate as an independent variable. We have done this by adding APPRATEB in models (4) and (6). Its significant negative sign indicates that racial differences in approval rates disappear as the black rate moves higher. Also, the R^2 is higher for these models, as would be expected.

[6] While this model does involve a limited dependent variable (i.e., a theoretical range from 0 to 1), the observations did not involve any extreme values (i.e., below .1 or over .9). Consequently, a linear specification was used to simplify the exposition and graphics (Figure 1). Moreover, the statistical conclusions drawn from the linear results were found to hold using other specifications (e.g., logit, linear-log, and reciprocal).

Table 2—Estimation Results: Unpooled Data (n = 51)

Model	1	2	3	4	5	6
Race	White	Black	Both	Both	Both	Both
Dependent Variable	APPRATE	APPRATE	DIFFAPP	DIFFAPP	DIFFAPP	DIFFAPP
Independent Variable:	Regression Coefficients (t-values in parentheses)					
(constant)	.30 (2.01)	.48 (3.66)	-.49 (-.772)	.11 (5.29)	.27 (1.36)	.50 (7.98)
AVEINCW	.00000074 (2.96)		.0000095 (2.48)	.0000043 (3.26)		
HOMEOWNW	.51 (2.88)		7.34 (1.16)	.59 (2.80)		
PERPOPW	-.006 (-.124)		.022 (.156)	-.018 (-.361)		
AVEINCB		.0000089 (3.07)	-.000017 (-3.447)	-.0000043 (-2.33)		
HOMEOWNB		-.196 (-.354)	.62 (1.00)	.25 (1.18)		
PERPOPB		-.086 (-.566)	-.203 (-.973)	-.11 (-1.52)		
BANKPROP	-1.70 (-.19)	-21.70 (-.84)	14.41 (.645)	.50 (.067)	11.93 (.49)	.48 (.063)
HOMEPRICG	.014 (1.08)	.006 (.176)	.02 (.491)	.015 (1.11)	-.0086 (-.263)	-.0013 (-.13)
DIFAVINC					.0000072 (1.75)	.0000041 (3.19)
DIFHMOWN					-.319 (-1.30)	.18 (2.24)
DIFFPOP					.12 (1.14)	.03 (1.00)
APPRATEB				-.79 (-18.33)		-.80 (-20.54)
F-value	5.78	3.61	2.49	57.18	1.24	80.99
R^2	.39	.29	.32	.93	.12	.92

Table 3—Estimation Results: Pooled Data (n = 102)

Model	1	2	3	4
Dependent Variable	APPRATE	APPRATE	APPRATE	APPRATE
Independent Variable:	Regression Coefficients (t-values in parentheses)			
(constant)	.42 (5.47)	.47 (5.52)	.42 (2.93)	.35 (3.74)
AVEINC	.0000056 (4.98)	.0000052 (4.40)	.0000091 (4.04)	.000010 (5.06)
HOMEOWN	.12 (4.91)	-.179 (-.836)	-.30 (-.86)	.002 (.009)
PERPOP	.12 (2.04)	.108 (1.92)	.06 (.71)	.08 (1.53)
BANKPROB	-15.51 (-1.10)	-15.96 (-1.14)	-19.82 (-1.03)	-14.59 (-1.09)
HOMEPRICG	.017 (.90)	.008 (.421)	.01 (.38)	.012 (.596)
WHITE		.25 (1.39)	-.12 (-.34)	.31 (1.77)
WHITE*AVEINC			-.0000069 (-2.49)	-.0000070 (-3.00)
WHITE*HOMEOWN			.81 (1.55)	
WHITE*PERPOP			-.06 (-.47)	
WHITE*BANKPROB			18.12 (.66)	
WHITE*HOMEPRICG			.003 (.08)	
F-value, partial[1]	-----	1.94	2.31	5.55
F-value[2]	33.63	28.62	17.80	27.88
R^2	.64	.64	.69	.67

[1] For independent variables below HOMEPRICG; [2] For all independent variables

An important statistical issue is whether the same model applies to both whites and blacks. That is, are the coefficients (intercept and slopes) in models (1) and (2) of Table 2 equal for each racial group. One way to test this is to pool the data for both groups and add a binary variable (WHITE = 1 if white, 0 if black). The estimation results in Table 3 are based on such a pooled data set of 102 observations. In model (1) the original model is estimated and all variables have the anticipated signs, with most being significant. In model (2) the binary variable is introduced; its coefficient indicates the white group has a 25 percent higher approval rate. This is larger than the difference in Table 1 (17 percent). In Table 3 the other variables have been controlled for in the multivariate model. Moreover, the coefficient of WHITE is statistically significant. Statistically, this significance means that we can reject the hypothesis that the intercepts in Table 2 are the same for whites (model 1) and blacks (model 2).

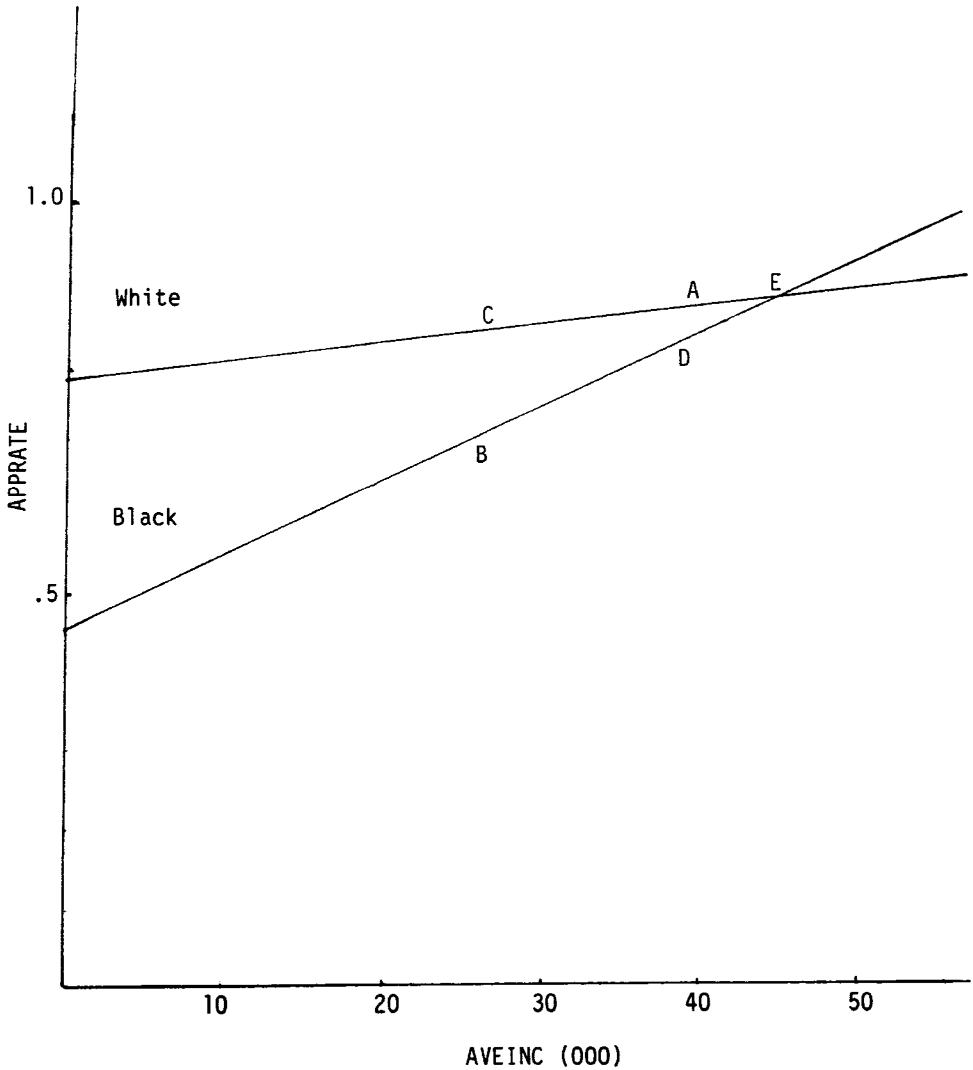
A more complete comparison of the models for whites and blacks requires testing to see if the slopes, as well as the intercepts, are equal for the two groups. One way to do this is to interact the binary variable, WHITE, with each of the independent variables.[7] This is done in model 3 of Table 3. The F-value (partial) of 2.31 is not significant at the 5 percent level. The five interaction variables also were tested alone, which yielded an even less significant F-value of 1.3 (not shown in Table 3). This means we cannot reject the hypothesis that the slopes of these interaction variables are all zero. Put another way, we conclude that white and black approval rates are affected by the independent variables in the same way.

While the interactions as a group are insignificant, the income interaction variable proved significant (t-value = -2.49) so it was used alone in model 4, Table 3. This result most clearly focuses on the independent variable (income) that has proven to be the most consistently significant in the various models. By allowing for the interaction (of income), it is possible to analyze more fully how differences in approval rates are related to differences in income levels. Also, the partial F-value (5.55) for the WHITE and WHITE*AVEINC variables is significant at the 1 percent level in model 4, Table 3.

The negative sign for the income interaction in model 4 suggests that approval for whites is influenced less by income than is approval for blacks. This is illustrated by Figure 1 which is graphed using mean values for all the independent variables except AVEINC. It shows a flatter slope for whites (in the relationship between income and approval rate) which indicates that approval rate differences vary with income levels.

[7] Another method often used to test for differences in coefficients between models and/or data sets is the Chow test.

Figure 1—The Relationship Between Approval Rates (APPRATE) and Average Income (AVEINC) by Race (based on Model 4, Table 3)



It should be noted that in model 2 (Table 3) the WHITE coefficient (+.25) is interpreted to mean that whites have a 25 percent higher approval rate than blacks and that this holds true for any income level. With the income interaction in Figure 1 we allow the approval differential to vary with income. The white and black lines intersect (point E), an interesting result. It means that if black and white incomes were both equal to $44,286, the approval rate difference would disappear. If both had incomes above $44,286, blacks would have higher approval rates. On the other hand, if both had no income (i.e., were at the left axis in Figure 1) the difference in approval rates would be 31 percent (.77-.46).

These possibilities involve extrapolation of the original data, however, in that income levels for both races are not this extreme (Table 1). The best measurement of the difference in approval rates using this model is found by predicting approval rates using the actual mean income levels of each racial group. This is shown graphically as the vertical distance between points A (for whites) and B (for blacks) in Figure 1. Numerically, the difference is 17 percent (.89-.72). This represents what difference there is given the existing difference in incomes between the races. Such a difference would not be considered discrimination. For discrimination to exist, the difference in approval rates would have to exist, given the same level of income. As seen in Figure 1, the amount of discrimination declines as income levels rise (to point E).

More generally, what Figure 1 indicates is that racial differences in approval rates could be reduced, or even eliminated, if white and black incomes were to be equalized. For example, if white incomes were lowered to black levels (i.e., from A to C in Figure 1), the approval differential would be reduced to 13 percent (.85-.72). While if black incomes were to rise to white levels (i.e., from B to D in Figure 1), the approval differential would be reduced to 4 percent (.89-.85). Finally, if incomes were equalized at a high enough level (point E in Figure 1) the approval rates would be the same for whites and blacks.

Taken together, the results in Figure 1 show that racial approval rates are based to some extent on racial income differences. Even if existing income differences are allowed for (i.e., points A and B in Figure 1), however, there is still a distinct racial difference in approval rates. The difference might be reduced or eliminated if incomes of the two races were equalized at a high enough level of income. Finally, the vertical gap in Figure 1 can be taken as a measure of racial discrimination in approval rates that is sensitive to income levels.[8] Somewhat encouraging is the realization that rising income levels for both groups will move us toward point E and the elimination of discrimination.

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[8] This is similar to measures of discrimination done by labor economists (e.g., measuring black/white gaps given the same level of training and tenure).

Conclusion

The recently released HMDA data indicate large racial differences in loan approval rates in all states. Whether such differences are the result of deliberate racial discrimination on the part of financial institutions or the consequence of racial differences in loan criteria has not been resolved, as yet.

While it would be ideal to have details regarding income, employment, credit history, and other loan criteria for each loan applicant, this will not be possible even when all the HMDA data are released. In this paper we have used census-based state and race-specific group data as a proxy for equivalent individual data. The results show, as expected, that loans are more likely to be approved in states with high income and this is true for both racial groups. Once income is accounted for, however, the racial difference in approval rates is still significant. Moreover, this difference, which is a measure of discrimination, is shown (Figure 1) to be related to the income levels of the two racial groups. It remains to determine if this aggregated result is a precursor of what microtesting will reveal about the nature of racial discrimination in home mortgage lending. It should be noted that migration studies, which have been estimated using both aggregated and microdata, have shown results to be consistent using both approaches (Greenwood, 1975).

The model specified allows for the introduction of bank characteristics and analysis of bank-specific approval rates. While the bank problem variable used has the anticipated sign in most of the results, it is not always significant. We hope that data specific to each bank will prove more successful in future work. Also, we hope to be able eventually to obtain individual loan applicant data that would allow for more definitive testing for racial discrimination in the approval of home loans.

Even in its present aggregated form the HMDA data are valuable because they provide, for the first time, information for both approved and rejected mortgage applications. Previous studies have relied on information about only those approved which limits the specification and estimation of decision models of the approval process. The model offered in this paper, using approval rates, is an aggregated version of such decision models that makes use of the information now available about both approved and rejected applicants. Similar aggregated models might be used later to consider whether racial discrimination can be linked to a particular bank and/or neighborhood. Eventually, the microdata for each applicant may be used to provide more definitive specification and testing. Even these models may incorporate variables based on the results provided by aggregated testing, however, such as has been offered in this paper.

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