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REDLINING IN BOSTON: DO MORTGAGE LENDERS DISCRIMINATE AGAINST NEIGHBORHOODS?*

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Historically, lenders have been accused of "redlining" minority neighborhoods as well as refusing to lend to minority applicants. Considerable bank regulation is designed to prevent both actions. However, the strong correlation between race and neighborhood makes it difficult to distinguish the impact of geographic discrimination from the effects of racial discrimination. Previous studies have failed to untangle these two influences, in part, because of severe omitted variable bias. The data set in this paper allows the distinct effects of race and geography to be identified, and it shows that the evidence for redlining is weak.

Mortgage lenders are often accused of refusing to extend credit in low-income and minority neighborhoods. When this traditional "redlining" occurs, white and minority applications in minority tracts are treated more harshly than their counterparts in white neighborhoods, even though applications by whites and minorities may be treated identically within each tract. In fact, concerns about redlining helped motivate some of the regulations imposed by the Community Reinvestment Act (CRA); for example, CRA makes lending in poor neighborhoods a requirement for merger approval. Whether such a policy is appropriate depends on the nature of any discrimination in mortgage lending: does it occur against individuals, locations, both, or neither? Prior attempts to test for redlining have been inconclusive because the data examined lacked variables vital to the mortgage lending decision. This study includes almost the entire information set of the lender. These new data provide evidence that lenders do not discriminate on the basis of the racial composition of the neighborhood, at least directly, although they may discriminate based on the race of the applicant. Therefore, laws such as CRA aimed at preventing geographic discrimination are unlikely to alter the racial disparities that occur in mortgage lending.

Previous studies of redlining have produced mixed results. Bradbury, Case, and Dunham [1989], Avery and Buynak [1981], Dedman et al. [1988], and Gabriel and Rosenthal [1991] find evi-

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dence that the volume of loans originated in minority tracts is significantly lower than one would expect given certain neighborhood characteristics. On the other hand, Bentson, Horsky, and Weingartner [1978], Canner, Gabriel, and Woolley [1991], and Schafer and Ladd [1981] find little evidence that different neighborhoods receive differential treatment. Most of these studies examine only accepted applications, and all of them omit property and applicant characteristics that are both important to the mortgage lending decision and correlated with either neighborhood characteristics or race. For this reason, the Federal Reserve Bank of Boston, with the help of the other regulatory agencies, surveyed a large sample of mortgage applications in the Boston MSA in an attempt to collect data on all the property, neighborhood, and individual characteristics necessary to determine whether redlining is occurring in the mortgage lending market.

Even with a complete data set, separating the effect of the racial composition of the neighborhood from that of the race of the applicant is difficult, since the two tend to be highly correlated. By including indicator variables for each neighborhood in every regression, Munnell, Tootell, Browne, and McEneaney [1996, hereinafter MTBM] isolate the role that race plays in the mortgage lending decision, controlling for the effect of geography. MTBM find that, within neighborhoods, race is an economically and statistically significant determinant in the mortgage lending decision, even after accounting for the additional variables collected in the extended survey.

Although discrimination based on the applicant's race is one obstacle to minority access to credit, discrimination based on the racial composition of the tract has historically been viewed as a more widespread problem. Yet, the tract indicator variables used in MTBM to control for all neighborhood effects cannot identify what these neighborhood characteristics are and what their relative importance may be. Using tract dummies to isolate the role race may play within each neighborhood makes it impossible to analyze the effect of any specific neighborhood characteristic, such as its racial composition. Thus, this study examines the other side of the coin. Instead of investigating the role of race on mortgage lending given all the characteristics of the neighborhood, here the importance of the racial composition of the neighborhood is examined controlling for the race of the applicant.

In fact, most previous empirical work and current bank regulation have been in response to concerns that tract-specific characteristics, such as its racial composition, are important in the mortgage lending decision. This paper shows that, with only one caveat, the racial composition of the tract where the property is located is not significantly related to the mortgage lending decision. Areas appear to be redlined only because they are inhabited by minorities. If more whites moved into minority neighborhoods, the rate of lending in these areas would tend to increase.

The first section of the paper discusses the data. Evidence is presented in Section II that the racial composition of the neighborhood plays little direct role in the mortgage lending decision, but the race of the applicant does. Section III shows that other tract characteristics often thought to be alternative grounds for redlining also appear to have little direct effect on mortgage lending. The fourth section examines an indirect route through which redlining may occur: lenders are more apt to require private mortgage insurance from applications in minority neighborhoods. Various possible interpretations of the coefficient on race are then examined in Section V. A conclusion follows.

I. Data: Past and Present

This study builds on the 1990 Home Mortgage Disclosure Act (HMDA) data for the Boston Metropolitan Statistical Area by adding an extensive follow-up survey. HMDA was enacted in 1975 in response to concerns voiced by community activists that banks had demarcated areas in cities where they were unwilling to make mortgage loans. The legislation required that banks report the number of mortgage loans made, by location of property. In fact, under CRA the volume of loan originations in low-income tracts found in the HMDA data is one criterion for merger approval. These data, however, were never particularly useful in evaluating lenders' performance, since information was collected only on loans accepted, not on applications made. It was unclear from the original HMDA data whether a small number of loan originations in a neighborhood were due to low mortgage demand or low credit supply in that area. Amendments to HMDA in 1989 required that lenders report not only the location of loans actually made but the location of loans denied, as well as the sex, race, and income level of all applicants. As a result, beginning in 1990 information became available about the applicant as well as the property and about applications denied as well as those approved.

TABLE I
MORTGAGE DENIAL RATES

	White tracts	Minority tracts	Total by race
White applicants	10% (2185)	17% (58)	10% (2243)
Minority applicants	24% (396)	33% (286)	28% (682)
Total by tract	12% (2581)	31% (344)	

Data source. HMDA data and 1990 Census of Population and Housing STF 1A. Numbers in parentheses are the sample size in each cell.

The 1990 HMDA data showed substantially higher denial rates in minority tracts than in white tracts. Various definitions of a minority neighborhood were examined; the predominant description used in this paper is a tract with over 30 percent minority population.[1] By this definition, 63 of the 524 tracts with mortgage applications in this study were minority neighborhoods. Table I shows that, in our sample, applicants in minority neighborhoods were almost three times as likely to be denied a loan as applicants in white areas, and minorities in general were almost three times as likely to be denied a mortgage as were whites. Both whites and minorities were more likely to be rejected when the property was located in a minority tract, as would be expected if redlining were occurring. The pattern of denials in the 1990 HMDA data only fueled the debate about both redlining and discrimination. Some people argued that the disparities were evidence of redlining and discrimination on the part of lenders. Others argued that because the HMDA data omit information on a host of factors that lenders consider in making mortgage decisions, any conclusions about redlining and racial discrimination were suspect.

In fact, the HMDA data include only one piece of economic

1. Alternative thresholds for the definition of a minority tract were examined in all the empirical work, and most of the estimation in the paper includes the minority population share, a continuous variable. The results are not sensitive to the choice of the threshold. The 30 percent level is selected because tracts were either heavily minority, above 80 percent, or heavily white, below 30 percent minority. The threshold is set low for two reasons. First, lenders may look at neighborhoods as white versus nonwhite tracts, suggesting that a low minority threshold may be relevant. Further, so few whites applied in tracts with a high minority composition that the power of many of the most interesting tests was very low when a higher threshold was set. It cannot, however, be rejected that the effect of being in a tract that is roughly 30 percent minority differs from being in one that is above 80 percent minority. It also cannot be rejected that blacks and Hispanics, or black tracts and Hispanic neighborhoods, are treated identically. As a result, the two groups are pooled.

information about the applicant—namely, income. Income alone actually has less explanatory power than one might expect, because lower income borrowers usually buy lower priced homes. Lenders put much more weight on measures of the applicant's ability to support the loan, such as the ratio of housing expense to income, the ratio of total debt to income, and the stability of the applicant's employment; on the applicant's commitment to debt repayment, as measured by credit history; on measures of potential loss, such as the loan-to-value ratio, the presence of private mortgage insurance, and the stability of the value of the mortgaged property; and on the characteristics of the property, such as single-family versus multifamily units.

To augment the 1990 HMDA report and capture the effect of these other variables on the mortgage lending decision, the Federal Reserve Bank of Boston gathered information on 38 additional variables from the lenders' files for a sample of applications in the Boston MSA. Variables quantifying several neighborhood characteristics were also taken from Census data to supplement the application information.[2] Most important, the Census data were used to calculate the racial composition of each tract. The sample was designed to include all 1210 mortgage applications by blacks and Hispanics in 1990 and a random sample of 3300 applications by whites.[3] Because the rejection rates for whites and in white tracts are so much lower than the corresponding minority rates, a larger number of applications from whites were required to provide the power necessary to compare white and minority rejections accurately.

Almost all of the information contained in the standard mortgage application form was gathered. Several other variables were taken from credit reports, lenders' worksheets, and the property appraisal. The additional variables collected were chosen after repeated conversations with mortgage loan officers and mortgage underwriters. Every variable these lenders indicated as important in their decision-making process was collected; the fact that they all felt the survey was far too inclusive is one indicator of its thoroughness. A list of the additional variables gathered and their mean values are presented in Tables II and III, for ap-

2. The 1990 Census of Population and Housing STF 1A is the source of all the Census data used in the study.

3. Only conventional, home-purchase loans were examined in order to avoid any complications that might arise from the potential use of different lending standards for refinances and government-guaranteed FHA/VA loans.

TABLE II

MEAN VALUES OF VARIABLES COLLECTED BY THE FOLLOW-UP SURVEY: BY TRACT

	White tracts		Black/Hispanic	
Tract mortgage application for properties located in:	Accepted	Rejected	Accepted	Rejected
Personal/financial characteristics				
1. Mean age of applicant	36.6	36.6	36.3	37.2
2. Mean age of coapplicant	26.1	23.6	20.5	19.6
3. Mean years of school (applicant)	15.5	14.9	13.9	13.7
4. Mean years of school (coapplicant)	10.5	9.27	7.3	7.2
5. Mean number of years in line of work (applicant)	10.8	9.94	7.72	8.43
6. Mean number of years in line of work (coapplicant)	8.1	7.76	6.86	5.28
7. Mean number of applicant dependents	0.75	0.88	0.92	0.88
8. Mean number of years on job (applicant)	6.64	5.98	5.80	5.44
9. Mean number of years on job (coapplicant)	5.12	5.33	4.94	4.06
10. Proportion self-employed	0.12	0.17	0.05	0.09
11. Mean base monthly income (applicant)	4374.6	4001.6	2477.7	2508.80
12. Mean base monthly income (coapplicant)	1378.6	1487.7	942.10	779.10
13. Mean total monthly income (applicant)	5008.8	4647.6	2816.1	2866.6
14. Mean total monthly income (coapplicant)	1490.8	1687.5	995.2	914.50
15. Mean proposed monthly housing expense ($)	1487.3	1510.9	1058.7	1107.10
16. Mean purchase price ($)	195,594	180,690	127,980	140,039
17. Mean value liquid assets ($)	89,990	118,870	22,710	24,730
18. Mean value total assets ($)	345,080	353,980	89,990	83,360
19. Mean of net worth	260.4	284.20	62.5	34.01
20. Mean total nonhousing monthly payments ($)	477.13	594.20	271.10	447.50
21. Mean value of total liabilities ($)	84,690	69,810	27,440	49,353
22. Mean obligation ratio (housing expense/income)	24.9	29.0	25.1	30.1
23. Mean total obligation ratio (total obligations/income)	32.1	39.45	32.4	41.7
24. Mean of unemployment region	3.78	4.12	3.67	3.92
25. Mean of probability of unemployment	0.19	0.22	0.24	0.22

Credit history				
26. Mean of no late mortgage payments	0.33	0.21	0.16	0.10
27. Mean of no mortgage payment history	0.64	0.72	0.84	0.89
28. Mean of one or two late mortgage payments	0.02	0.03	0.00	0.02
29. Mean of more than two late mortgage payments	0.008	0.03	0.004	0.00
30. Mean of no "slow pay" consumer account	0.61	0.32	0.53	0.25
31. Mean of one or two slow pay consumer accounts	0.18	0.17	0.13	0.10
32. Mean of more than two slow pay consumer accounts	0.05	0.08	0.05	0.11
33. Mean of insufficient consumer credit history	0.03	0.05	0.09	0.15
34. Mean of delinquent consumer credit history	0.07	0.14	0.08	0.18
35. Mean of serious consumer delinquencies	0.06	0.24	0.12	0.21
36. Proportion with public records	0.05	0.27	0.06	0.23
37. Mean number of commercial credit reports on file	1.48	1.55	1.45	1.38
38. Mean number of credit lines on report	13.4	14.2	9.27	9.50
Loan and property characteristics				
39. Fixed loan	0.66	0.64	0.67	0.75
40. Term (months)	346	350	356	357
41. Proportion for special programs	0.03	0.04	0.28	0.32
42. Mean appraised value of property ($)	240,880	184,072	139,513	145,632
43. Proportion denied private mortgage insurance	0.001	0.14	0.008	0.25
44. Mean of loan-to-value ratio*	0.75	0.84	0.85	0.89
45. Mean number of units in property purchased*	1.12	1.25	1.58	1.86
Neighborhood characteristics				
46. Mean of rent to value in tract**	0.08	0.13	0.16	0.14
47. Median income in tract**	55,669	52,445	28,830	28,744
48. Boarded-up rate**	0.02	0.02	0.10	0.09
49. Vacancy rate**	0.06	0.06	0.10	0.10
50. Number of white applicants*	1965	220	48	10
51. Number of black/hispanic applicants*	299	97	191	95

Percentage base for each item does not include applicants for whom information was missing.

*Source of the data is the original HMDA survey. **Source of the data is the Census Survey. All other data, plus part of the data used to construct line 44, are from the extended survey.

TABLE III

VALUES OF VARIABLES COLLECTED ON 1992 FOLLOW-UP SURVEY

	Applications by whites		Applications by blacks/ Hispanics	
Characteristic	Accepted	Rejected	Accepted	Rejected
Personal/financial characteristics				
1. Mean age of applicant	36	36	37	37
2. Mean age of coapplicant	26	22	24	23
3. Mean years of school (applicant)	16	15	14	14
4. Mean years of school (coapplicant)	11	9	9	9
5. Mean number of applicant dependents	0.71	0.82	0.98	0.94
6. Mean number of years in line of work (applicant)	11	11	9	8
7. Mean number of years in line of work (coapplicant)	8	9	7	6
8. Mean number of years on job (applicant)	7	6	6	5
9. Mean number of years on job (coapplicant)	5	6	5	4
10. Proportion self-employed	0.12	0.22	0.08	0.07
11. Mean base monthly income (applicant)	4,439	4,150	3,186	3,008
12. Mean base monthly income (coapplicant)	1,378	1,475	1,169	1115
13. Mean total monthly income (applicant)	5,096	4,911	3,581	3359
14. Mean total monthly income (coapplicant)	1,484	1,684	1,276	1269
15. Mean proposed monthly housing expense ($)	1,499	1,579	1,229	1209
16. Mean purchase price ($)	198,000	189,000	151,000	149,000
17. Mean value liquid assets ($)	94,000	140,000	40,000	43,000
18. Mean value total assets ($)	365,000	442,000	139,000	101,000
19. Mean of net worth	275,000	354,000	103,000	64,000
20. Mean total nonhousing monthly payments ($)	474	588	391	522
21. Mean value of total liabilities ($)	90,000	88,000	36,000	37,000
22. Mean obligation ratio (housing expense/income)	24.80	29.50	25.20	29.0
23. Mean total obligation ratio (total obligations/income)	32.00	40.32	32.83	39.69
24. Mean of unemployment region	3.81	4.37	3.61	3.71
25. Mean of probability of unemployment	0.19	0.22	0.23	0.23
Credit history				
26. Mean of no late mortgage payment	0.35	0.25	0.17	0.09
27. Mean of one or two late mortgage payments	0.01	0.04	0.01	0.02

28. Mean of no mortgage payment history	0.63	0.67	0.81	0.87
29. Mean of more than two late mortgage payments	0.01	0.03	0.00	0.02
30. Mean of no "slow pay" consumer account	0.62	0.37	0.53	0.21
31. Mean of one or two slow pay consumer accounts	0.19	0.19	0.13	0.11
32. Mean of more than two slow pay consumer accounts	0.05	0.08	0.08	0.10
33. Mean of insufficient consumer credit history	0.02	0.03	0.07	0.13
34. Mean of delinquent consumer credit history	0.07	0.11	0.08	0.20
35. Mean of serious consumer delinquencies	0.05	0.21	0.12	0.26
36. Proportion with public records	0.04	0.22	0.09	0.31
37. Mean number of commercial credit reports on file	1	2	2	1
38. Mean number of credit lines on report	14	15	11	11
Loan and property characteristics				
39. Fixed loan	0.68	0.66	0.60	0.69
40. Mean term	345.0	346.84	356.27	357.79
41. Special programs	0.03	0.03	0.17	0.20
42. Mean appraised value of property ($)	208,000	192,000	159,000	153,000
43. Proportion denied private mortgage insurance	0.00	0.15	0.00	0.18
44. Mean of loan-to-value ratio*	0.74	0.83	0.85	0.88
45. Mean number of units in property purchased*	1.12	1.25	1.36	1.58
Neighborhood characteristics				
46. Mean of rent-to-value ratio in tract**	0.08	0.10	0.12	0.17
47. Median income in tract**	56,091	54,767	40,279	36,891
48. Boarded-up rate**	0.02	0.02	0.06	0.05
49. Vacancy rate**	0.06	0.06	0.07	0.08
50. Number in minority tracts*	48	10	191	95
51. Number in white tracts*	1965	220	299	97

Percentage base for each item does not include applicants for whom information was missing.

*Source of the data is the original HMDA survey. **Source of the data is the Census Survey. All other data, plus part of the data used to construct line 44, are from the extended survey.

plications for properties in minority and white tracts, accepted and denied, and for applications from minorities and whites, accepted and denied.

Tables II and III highlight that differences do exist between mortgage applications from white and minority tracts and applications from whites and minorities. For example, the tables reveal that both applications from minority tracts and applications from minorities tend to have higher loan-to-value ratios than do applications from white tracts and applications from whites. Minorities and applicants for properties in minority tracts also tend to have weaker credit histories and lower income and net wealth than whites and applicants for properties in white tracts. On the other hand, similar patterns of debt-to-income ratios for rejected and accepted applications are found across all four groups. The data in Tables II and III suggest an economic basis for at least some of the difference in the loan rejection rates found between applications for properties located in minority tracts and those for properties in white tracts, as well as for applications by minorities and applications by whites. The importance of these variables in the mortgage lending decision must, however, be examined in order to determine the extent to which these economic distinctions can explain the different denial rates.

Table IV shows that the divergence of these denial rates cannot be explained using only the HMDA data.[4] The four columns present the coefficients from logistic regressions and linear probability models that estimate the probability of denial based solely on the information collected for the Home Mortgage Disclosure Act and the Census data. Estimates from the logistic regressions are included because they produce consistent estimates of the standard errors and efficient estimates of the coefficients. Estimates from the linear probability models are presented because they are easily interpreted. For all regressions in this paper, the standard errors in both the logits and the linear probability models are corrected for heteroskedasticity and for grouped errors at the tract level. The minority status of the tract is measured two ways—as a dummy variable indicating whether the tract is more than 30 percent black and Hispanic, and as a continuous variable representing the percentage of the tract's population that is black

4. Several of the independent variables examined in the paper are missing some observations. The sample analyzed in each regression is as large as possible once these missing observations are excluded from the analysis. As a result, the sample size varies slightly across some of the tables.

TABLE IV
DETERMINANTS OF MORTGAGE LENDING: TESTS OF REDLINING USING THE ORIGINAL HMDA DATA

Dependent variable = 1 if application is denied	Logit		Linear probability	
Constant	−2.46	−2.48	0.06	0.06
	(−17.8)	(−17.8)	(3.60)	(3.36)
Loan amount/income	0.10	0.10	0.02	0.02
	(2.02)	(2.03)	(2.24)	(2.25)
Jumbo	0.24	0.24	0.03	0.03
	(1.39)	(1.42)	(1.22)	(1.25)
Personal and tract characteristics				
Female	−0.08	−0.09	−0.009	−0.01
	(−0.55)	(−0.64)	(−0.53)	(−0.63)
Minority tract	0.44		0.08	
	(2.60)		(2.55)	
% minority in neighborhood		0.006		0.001
		(3.32)		(3.28)
Race	1.06	1.02	0.15	0.14
	(7.92)	(7.38)	(6.76)	(6.14)
Log likelihood	−1100.6	−1100.0		
Adjusted R^2			0.06	0.06
Number of observations	2866	2866	2866	2866

Jumbo = 1 if the amount of the loan is greater than $192,000 and zero otherwise. Minority tract = 1 if the population of the tract is over 30 percent minority and zero otherwise. t-statistics, adjusted for heteroskedasticity and for grouped errors at the tract level, are in parentheses.

or Hispanic. Measured either way, the racial composition of the tract appears to play a statistically significant role in the lending decision, even when the race of the applicant is included in the regression. Whether the variation in rejection rates across these neighborhoods is due to different distributions of creditworthy applicants in these areas or to redlining, however, is impossible to ascertain without accounting for the other economic variables relevant to the mortgage lending decision.

II. DO MORTGAGE LENDERS REDLINE?

Lenders can redline along several possible dimensions including the racial composition of the neighborhood, the income level of the tract, and the boarded-up and vacancy rates in the area. Because these neighborhood characteristics may be correlated, the effect all these variables have on the probability of receiving a mortgage denial will be examined.

Table V presents logistic regressions and linear probability models testing the role that the racial composition of the tract plays in the mortgage lending decision once all the relevant variables collected in the survey are included in the analysis.[5] If minority neighborhoods are being redlined, rejection rates in these areas would be higher than expected, even after accounting for the important information in the mortgage file. In columns 1, 2, 5, and 6, the coefficients on both measures of a tract's minority status reveal that applications for properties in minority areas have a rejection rate about six percentage points higher than similar applications in white tracts. These results support the conclusion that redlining is occurring.

Lenders may appear to be redlining, however, only because the race of the applicant is both important in the mortgage lending decision and correlated with the minority composition of the tract. As a result, columns 3, 4, 7, and 8 control for the applicant's race in order to isolate any redlining of minority areas. With the race of the applicant included, the coefficient measuring lender redlining becomes insignificant. On the other hand, the estimated coefficient on race is significant in all four equations. Apparently, the minority tract coefficient was significant in equations 1, 2, 5, and 6 only because a disproportionate share of the applications in these tracts were from minorities. This evidence suggests that discrimination based on the race of the applicant, not the racial composition of the neighborhood, is occurring.

It is also possible that the applicant's race or the racial composition of the neighborhood is correlated with omitted personal characteristics relevant to the mortgage lending decision. Thus, the coefficients from reestimates of equations 3, 4, 7, and 8 in

5. The debt and loan-to-value ratios, credit history, local labor market conditions, type of building purchased, and race of the applicant are all important determinants of the lender's decision to approve or deny a loan. The loan-to-value ratio is separated into three segments, with thresholds at 80 and 95 percent. MTBM examines the importance of all the variables collected in the survey. The most robust specification is presented in Table V. The base results are, however, robust to a wide variety of specifications. For example, the probability of experiencing a spell of unemployment was calculated in several ways depending on the applicant's occupation, industry, and personal characteristics, with no effect on the differential in rejection rates between minorities and whites. Further, none of the different functional specifications examined, including nonlinear threshold effects around the secondary market standards for the housing expense-to-income ratio, the total obligations-to-income ratio, and the loan-to-value ratio, as well as other nonlinear and interactive relationships of the variables, altered the findings for the coefficient on race or minority tract. A complete discussion of the other variables in the survey found to be insignificant in the loan denial equation, and of the different specifications examined, can be found in MTBM.

TABLE V

TESTS OF MORTGAGE REDLINING INCLUDING THE VARIABLES FROM THE EXTENDED SURVEY

Dependent variable = 1 if application is denied	Logit				Linear probability			
	Redlining excluding race		Redlining and race		Redlining excluding race		Redlining and race	
Constant	−6.58	−6.60	−6.62	−6.63	−0.21	−0.22	−0.21	−0.21
	(−10.40)	(−10.40)	(−10.5)	(−10.5)	(−6.71)	(−6.79)	(−6.78)	(−6.83)
Ability to support loan								
Housing expense	0.46	0.46	0.45	0.45	0.06	0.06	0.06	0.06
	(3.14)	(3.15)	(3.04)	(3.04)	(3.60)	(3.60)	(3.53)	(3.53)
Total debt payments/income	0.05	0.05	0.05	0.05	0.005	0.005	0.005	0.005
	(5.06)	(5.09)	(5.12)	(5.13)	(6.36)	(6.35)	(6.37)	(6.38)
Net wealth	0.00007	0.00007	0.00009	0.00008	0.000008	0.000008	0.000009	0.00009
	(1.96)	(1.88)	(2.33)	(2.29)	(1.82)	(1.84)	(1.89)	(1.89)
Unemployment region	0.07	0.07	0.08	0.08	0.007	0.007	0.007	0.007
	(2.32)	(2.28)	(2.64)	(2.61)	(2.13)	(2.12)	(2.31)	(2.30)
Self-employed	0.41	0.41	0.42	0.46	0.04	0.04	0.04	0.04
	(2.19)	(2.21)	(2.25)	(2.26)	(2.20)	(2.20)	(2.23)	(2.23)
Consumer credit history								
One or two slow pay accounts	0.64	0.64	0.64	0.64	0.04	0.04	0.04	0.04
	(3.54)	(3.52)	(3.54)	(3.53)	(3.10)	(3.03)	(3.09)	(3.08)
More than two slow pay accounts	0.87	0.86	0.78	0.78	0.06	0.06	0.06	0.06
	(3.22)	(3.19)	(2.83)	(2.83)	(2.18)	(2.14)	(1.92)	(1.91)

(*continues*)

TABLE V

TESTS OF MORTGAGE REDLINING INCLUDING THE VARIABLES FROM THE EXTENDED SURVEY (CONTINUED)

Dependent variable = 1 if application is denied	Logit				Linear probability			
	Redlining excluding race		Redlining and race		Redlining excluding race		Redlining and race	
Insufficient credit	1.59	1.58	1.51	1.51	0.15	0.15	0.15	0.14
history	(5.71)	(5.74)	(5.47)	(5.51)	(4.10)	(4.10)	(3.89)	(3.91)
Delinquencies	1.34	1.32	1.30	1.30	0.13	0.13	0.13	0.13
	(6.38)	(6.31)	(6.20)	(6.18)	(5.02)	(5.0)	(4.96)	(4.95)
Serious	1.63	1.62	1.58	1.57	0.19	0.19	0.18	0.18
delinquencies	(8.60)	(8.49)	(8.20)	(8.17)	(6.94)	(6.86)	(6.73)	(6.70)
Mortgage credit history								
No mortgage	0.34	0.33	0.30	0.30	0.02	0.02	0.02	0.02
history	(1.90)	(1.82)	(1.65)	(1.62)	(1.96)	(1.87)	(1.67)	(1.64)
One or two slow	0.69	0.68	0.66	0.66	0.06	0.06	0.06	0.06
accounts	(1.50)	(1.49)	(1.42)	(1.42)	(1.03)	(1.02)	(1.00)	(1.00)
More than two late	1.17	1.17	1.15	1.15	0.15	0.15	0.15	0.15
payments	(2.35)	(2.32)	(2.32)	(2.31)	(1.75)	(1.75)	(1.74)	(1.74)
Public record	1.32	1.33	1.24	1.25	0.21	0.21	0.20	0.20
history	(7.09)	(7.12)	(6.68)	(6.68)	(6.63)	(6.65)	(6.42)	(6.43)
Property characteristics								
Two- to four-family	0.49	0.48	0.44	0.43	0.05	0.05	0.05	0.05
home	(2.95)	(2.90)	(2.60)	(2.57)	(2.72)	(2.65)	(2.34)	(2.31)
Not owner-occupied	1.06	1.05	1.13	1.12	0.10	0.10	0.10	0.10
	(3.28)	(3.26)	(3.50)	(3.49)	(2.89)	(2.89)	(3.01)	(3.00)

Terms of loan								
Denied private mortgage insurance	4.53	4.53	4.58	4.58	0.67	0.66	0.67	0.67
	(8.39)	(8.37)	(8.43)	(8.43)	(18.6)	(18.7)	(18.8)	(18.9)
Loan/appraised value: low	1.19	1.19	1.15	1.15	0.03	0.03	0.02	0.02
	(1.67)	(1.66)	(1.63)	(1.62)	(0.75)	(0.74)	(0.63)	(0.63)
Loan/appraised value: medium	1.36	1.35	1.23	1.23	0.06	0.05	0.04	0.04
	(2.30)	(2.27)	(2.12)	(2.11)	(1.68)	(1.65)	(1.33)	(1.33)
Loan/appraised value: high	1.57	1.53	1.43	1.43	0.10	0.09	0.09	0.08
	(2.71)	(2.64)	(2.50)	(2.48)	(2.47)	(2.35)	(2.17)	(2.13)
Tract characteristics								
Minority tract	0.50		0.16		0.06		0.02	
	(3.01)		(0.88)		(3.02)		(1.00)	
Percentage of minority in neighborhood		0.008		0.003		0.001		0.0004
		(3.81)		(1.29)		(3.85)		(1.33)
Personal characteristics								
Race			0.63	0.60			0.07	0.07
			(3.72)	(3.51)			(3.57)	(3.31)
Log likelihood	−845.3	−844.1	−838.0	−837.8				
Adjusted R^2					0.29	0.29	0.29	0.29
Number of observations	2925	2925	2925	2925	2925	2925	2925	2925

*t-statistics, adjusted for heteroskedasticity and for grouped errors at the tract level, are in parentheses.

Table V when the applicant's age, education, marital status, number of dependents, and gender are added to the analysis are presented in Table VI. Only the coefficients of these additional variables are displayed in Table VI since their inclusion has little effect on the estimates of the other parameters. Of these other personal characteristics, only the applicant's marital status is significant. Again, however, the race of the applicant and not the racial composition of the tract is important in the mortgage lending decision.

It is difficult to unravel the effects of race from redlining when minorities are geographically clustered, yet minority applications in the Boston sample were not overly concentrated in minority areas. Well over 50 percent of all minority applications were for properties located in white areas. The evidence in Tables V and VI strongly suggests that the race of the applicant, not the racial composition of the neighborhood, is important in the mortgage lending decision.

A misspecification of the equations in Tables V and VI could explain the failure to find evidence of redlining. The racial composition of the tract may have a highly nonlinear effect on mortgage lending. Specifically, lenders may be particularly averse to loans from areas with a minority population share above some threshold level other than 30 percent. Alternatively, geographic discrimination may take on a more subtle form: race and the racial composition of the neighborhood may interact in the mortgage lending decision. Lenders may be steering minority applicants away from white neighborhoods, resulting in minority applicants in white areas being treated more harshly than minority applicants in minority areas—and perhaps the reverse for whites.[6]

Table VII examines both these hypotheses by adding the relevant variables to the base regression in Table V. Again, only the relevant coefficients are presented. Columns 1 and 4 include additional dummy variables indicating tracts with minority population shares from 30 to 50 percent and 51 to 70 percent. The minority tract variable is still insignificant, as are the coefficients on the different subranges. Allowing for this nonlinear reaction to minority concentration levels also has no effect on the size or significance of the coefficient on the applicant's race.[7]

6. Although real estate agents have frequently been accused of steering, mortgage lenders might be less likely to indulge in this practice since their involvement in the purchase is less visible.

7. The same results occur if deciles are used when creating the different composition dummies.

TABLE VI
COEFFICIENT ESTIMATES OF INDIVIDUAL CHARACTERISTICS

Dependent variable = 1 if application is denied	Logit		Linear probability	
Tract characteristics				
Minority tract	0.09		0.02	
	(0.46)		(0.64)	
% of minority tract		0.002		0.0002
		(0.63)		(0.79)
Personal characteristics				
Education	−0.04	−0.04	−0.003	−0.003
	(−1.83)	(−1.80)	(−1.38)	(−1.36)
Single	0.34	0.33	0.03	0.03
	(2.05)	(2.00)	(2.08)	(2.05)
Number of dependents	0.008	0.007	0.0002	0.0002
	(0.13)	(0.12)	(0.04)	(0.03)
Age	0.006	0.006	0.0005	0.0005
	(0.75)	(0.76)	(0.75)	(0.74)
Female	−0.21	−0.21	−0.02	−0.02
	(−1.16)	(−1.18)	(−1.23)	(−1.25)
Race	0.61	0.59	0.07	0.07
	(3.51)	(3.40)	(3.38)	(3.22)
Log of Likelihood	−817.03	−817		
Adjusted R^2			0.29	0.29
Observations	2872	2872	2872	2872

*t-statistics, adjusted for heteroskedasticity and for grouped errors at the tract level, are in parentheses.

Lenders may be discriminating against minorities, discriminating against minority tracts, or steering minorities (whites) to minority (white) neighborhoods. In columns 2 and 5 the interactive effects are added to the base model, while columns 3 and 6 further include both the interactive effects and additional personal characteristics of the applicant. The interactive coefficient measures the degree of steering in the sample and should be negative if minorities are being directed toward minority neighborhoods. In none of the equations presented is the coefficient measuring potential steering statistically significant. Further, since racial steering could mask redlining when the interactive term is omitted, it is interesting to note that the coefficient on the minority neighborhood indicator variable remains insignificant. These results are robust to whatever threshold level of minority share is chosen as the definition of a minority tract. Discrimina-

TABLE VII

ALTERNATIVE SPECIFICATIONS FOR REDLINING

Dependent variable = 1 if application is denied	Logit: Nonlinear redlining[a]	Logit: Steering, redlining, and discrimination[a]	Logit: Steering, redlining, and discrimination, including additional personal characteristics[b]	Linear probability: Nonlinear redlining[a]	Linear probability: Steering, redlining, and discrimination[a]	Linear probability: Steering, redlining, and discrimination, including additional personal characteristics[b]
Tract characteristics						
Minority share: 50%–75%	−0.02			0.02		
	(−0.05)			(0.32)		
Minority share: 30%–50%	−0.18			−0.02		
	(−0.52)			(−0.43)		
Minority tract	0.22	0.38	0.34	0.03	0.02	0.02
	(1.05)	(0.95)	(0.86)	(1.00)	(0.57)	(0.45)
Minority tract × race		−0.27	−0.31		0.001	−0.004
		(−0.54)	(−0.64)		(0.02)	(0.07)
Personal characteristics						
Race	0.62	0.66	0.64	0.07	0.07	0.07
	(3.68)	(3.70)	(3.53)	(3.46)	(3.26)	(3.14)
Log likelihood	−837.9	−837.8	−816.8			
Adjusted R^2				0.29	0.29	0.29
Number of observations	2925	2925	2872	2925	2925	2872

a. These additional tract and race variables are added to the base equation in Table V. Only the relevant coefficients are presented. t-statistics, adjusted for heteroskedasticity and for grouped errors at the tract level, are in parentheses.

b. These additional tract and race variables are added to the base equation in Table V along with the personal characteristics of gender, marital status, number of dependents, age, and education. Only the relevant coefficients are presented.

tion, not redlining or steering, appears to be occurring in the mortgage market in Boston.

Most of the unexplained difference between the denial rates in the two types of tracts is due to the unexplained difference between the denial rates for minority applications in both types of tracts. The economic variables in these equations consistently underpredict the actual minority denial rate by about eight percentage points, in both white and minority tracts. It is the race of the applicant that affects the mortgage lending decision; the location of the applicant's property appears far less relevant.

III. The Possibility of Nonracial Redlining

Although redlining is traditionally viewed as a refusal by banks to lend in areas with large minority populations, lenders may also avoid dilapidated or low-income neighborhoods, regardless of the race of the residents. That is, redlining need not be based on the racial composition of the neighborhood but could be based on other attributes of the tract. In fact, tracts with high rates of vacancy and boarded-up property, as well as those with many low-income residents, do have higher actual rejection rates. Table VIII presents tests for these alternative forms of redlining. Equations 1 to 6 in Table VIII add to the base equation such tract-specific variables as the rent-to-value ratio for property in the area, the median income level of households in the neighborhood, and the vacancy and boarded-up rates in the tract.[8] Only the rent-to-value ratio of property in the tract is significant in the lending decision, suggesting that the higher the rent-to-value, the higher the asset risk, and the higher the probability that an application will be denied.

The inclusion of these additional tract variables has no effect on the results on discrimination, redlining, or steering. Both measures of the racial composition of the tract are still statistically

8. Several observations are lost in regressions using the Census median tract income variable because of missing data. The boarded-up and vacancy rates are dummy variables equal to one when the tract's value of these variables is over two standard deviations above the mean. The median income variable in the tract is a dummy variable indicating when the value of this variable is a standard deviation below the sample mean. The results do not depend on the thresholds chosen or even whether the variables are used continuously. One justification for using indicator variables, however, is that these variables attempt to capture asset-price risk. Since lenders would only share in the losses, not the gains, from asset price changes, they are disproportionately concerned about the lower tails of the asset price risk.

TABLE VIII

REDLINING BASED ON ALTERNATIVE TRACT CHARACTERISTICS

Dependent variable = 1 if application is denied	Logit			Linear probability		
Tract characteristics						
High boarded-up rate[a]	0.12	0.08	0.14	−0.01	−0.02	−0.01
	(0.47)	(0.31)	(0.52)	(−0.37)	(−0.55)	(−0.36)
High vacancy rate[a]	−0.16	−0.17	−0.15	−0.01	−0.01	−0.01
	(−0.50)	(−0.53)	(−0.47)	(−0.53)	(−0.58)	(−0.53)
Low income[a]	0.03	−0.003	0.02	0.002	−0.002	0.002
	(0.10)	(−0.01)	(0.07)	(0.08)	(−0.05)	(0.08)
Rent/value	0.60	0.60	0.60	0.07	0.07	0.07
	(3.15)	(3.12)	(3.14)	(2.15)	(2.13)	(2.15)
Minority tract	0.08		0.29	0.02		0.02
	(0.28)		(0.62)	(0.49)		(0.34)
% of minority in tract		0.002			0.0004	
		(0.54)			(0.81)	
Minority tract × race			−0.26			(0.0001)
			(−0.51)			(0.002)
Personal characteristics						
Race	0.62	0.60	0.65	0.07	0.07	0.07
	(3.67)	(3.49)	(3.66)	(3.58)	(3.31)	(3.27)
Log of Likelihood	−745.3	−745.2	−745.2			
Adjusted R^2				0.31	0.31	0.31
Observations	2615	2615	2615	2615	2615	2615

a. High boarded-up rate and high vacancy rate refer to boarded-up rates and vacancy rates greater than 0.12 and 0.16, respectively. Low income refers to median tract incomes less than $34,000. These additional tract and race variables are added to the base equation in Table V. Only the relevant coefficients are presented. t-statistics, adjusted for heteroskedasticity and for grouped errors, at the tract level, are in parentheses.

insignificant, and the coefficients on the race and minority tract interactive variable in columns 3 and 6 show little evidence of steering. Omitted tract characteristics do not seem to explain the lack of evidence of redlining. Furthermore, there is little evidence that redlining is occurring along other characteristics of the tract. The difference in rejection rates between tracts that vary along any one of these neighborhood traits is explained by the economic characteristics of the applicants for properties in these different tracts. The influence of tract characteristics is either very slight or is not well captured by the Census data.

IV. Indirect Forms of Redlining

The data indicate that lenders are not redlining minority neighborhoods when deciding whether to grant a mortgage loan, but this finding is not sufficient to conclude that the racial composition of the tract plays no role in the mortgage lending process. Forcing an applicant to seek private mortgage insurance (PMI) can be an important part of the mortgage decision, since an application rejected for PMI almost always is rejected for the loan, and applications accepted for PMI must pay more for the loan. PMI is discussed in detail in Canner and Passmore [1994] and Tootell [1995b]. Essentially, private mortgage insurance is purchased by the borrower to protect the lender from losses caused by asset price deflation and foreclosure costs. Since PMI is costly, if applications for loans on properties in minority tracts, or from minorities, are more likely to be forced to acquire PMI, the redlining, or discrimination, would be in terms of price rather than action taken.

In order to test this hypothesis, the determinants of the lender's decision to require PMI must be examined. PMI is usually demanded when the down payment is less than 20 percent of the assessed value of the property and the loan is to be sold in the secondary market.[9] The importance of these secondary market guidelines should be captured by the thresholds used to define the different segments of the loan-to-value ratio in all the regressions presented in this paper.[10] Yet, the loan-to-value need not be

9. On rare occasions in 1990 the secondary market would purchase mortgages with loan-to-value ratios above 80 percent and no PMI.

10. Loan-to-value ratios of 80 percent and 95 percent represent the thresholds for the secondary market guidelines for requiring PMI and, generally, rejecting a loan even with PMI. As a result, the thresholds chosen for the segments of the loan-to-value ratio in every regression, 80 and 95 percent, should capture the importance of these secondary market standards for PMI.

all that determines whether PMI is required. If the loan is to be held in the bank's portfolio, applicants may be forced to acquire PMI even if the down payment is greater than 20 percent or, conversely, the lender may eschew PMI even if the down payment is less than 20 percent. Since much more discretion is involved when deciding whether to require PMI for portfolio loans, other variables besides the loan-to-value ratio could also be significant in the decision. Essentially, the lender's request for PMI will depend on its assessment of the expected costs and risks of a default; thus, many of the determinants of the mortgage decision might also help explain the decision to require PMI.

In fact, the major determinant of whether PMI is requested is whether the loan-to-value ratio is greater than 80 percent, as one would expect given the secondary market guideline. A poor mortgage history and low net wealth also increase the odds that PMI will have to be sought. Other tract characteristics, like the boarded-up and vacancy rates, tend to have the expected effect on the decision. Yet, holding all these economic and personal variables constant, the racial composition of the tract significantly helps to explain whether PMI is required.[11]

Possible redlining in the decision to require PMI raises concerns about whether the variable in the base regression indicating that PMI was denied is masking redlining in the mortgage lending decision. The relevant coefficients of the base equation are reproduced in columns 1 and 4 of Table IX. The specification includes the dummy variable indicating a PMI rejection; inclusion of this variable essentially eliminates an assignment of lender responsibility for denials by mortgage insurers. Alternatively, columns 2 and 5 present the coefficients of interest from a mortgage denial regression when lenders are given responsibility for PMI denials. The size of the coefficient on the minority tract

11. Lenders may be redlining minority neighborhoods indirectly by forcing applicants from these tracts to acquire PMI. Yet, it is also possible that applications that otherwise would have been rejected are given an extra chance if they qualify for PMI. In such a case, this indirect form of redlining would represent not an added burden for applicants in these areas, but another chance. To test whether PMI is being used as a boost rather than an added hurdle to applications from minority areas, the sample was divided into applications with very low loan-to-value ratios, strong credit histories, and low obligation ratios, and those with weak values for these variables. If seeking PMI represents an extra chance for applicants from minority neighborhoods, the coefficient on the minority tract variable in the decision to require PMI would be larger for the weaker applications. On the contrary, this coefficient is larger in the subsample of stronger applications. Apparently lenders are not helping weaker applications in minority tracts by requiring them to get PMI but are imposing a higher price on stronger applications that happen to be for properties located in minority areas.

TABLE IX

REDLINING AND THE DECISION TO REQUIRE PRIVATE MORTGAGE INSURANCE

	Logit			Linear probability		
Dependent variable = 1 if application is denied			Omitting observations denied PMI			Omitting observations denied PMI
Tract characteristics						
Denied private mortgage insurance	4.58			0.67		
	(8.43)			(18.8)		
Minority tract	0.16	0.30	0.19	0.02	0.05	0.03
	(0.88)	(1.69)	(1.02)	(1.00)	(1.91)	(1.19)
Personal characteristics						
Race	0.63	.54	0.62	0.07	0.07	0.07
	(3.72)	(3.38)	(3.71)	(3.57)	(3.25)	(3.46)
Log of Likelihood	−838.00	−923.9	−820.00			
Adjusted R^2				0.29	0.21	0.20
Number of observations	2925	2925	2850	2925	2925	2850
% of correctly predicted						

*t-statistics, adjusted for heteroskedasticity and for grouped errors at the tract level, are in parentheses.

indicator variable increases when the denied PMI variable is omitted, and it approaches statistical significance at the 5 percent level, which is consistent with the idea that the PMI decision is hiding redlining. Finally, columns 3 and 6 drop these PMI rejections from the sample altogether. This specification examines lender behavior when PMI rejections are not an issue at all. The size of the coefficient on the minority tract variable declines without the PMI denials, and it no longer is near significant at the 5 percent level.[12] Including the other tract variables in this analysis has no effect on these basic results. Thus, any evidence of redlining in mortgage denials is contained in the PMI denials.

Theory is not clear about how best to specify PMI's role in the mortgage lending decision.[13] Including a dummy variable to indicate whether an application was denied PMI gives the lenders credit for granting basically every loan in a minority area once PMI is acquired, even though they were forced to acquire PMI. Omitting that variable makes the lenders alone responsible for that rejection. In truth, lenders share responsibility for these rejections.

There is little evidence that the racial composition of the tract directly increases the probability that a mortgage will be denied. However, some evidence suggests that the decision to require PMI depends on the minority composition of the tract. This indirect form of redlining would increase the price paid by applications from these areas.

V. The Effect of Race

The racial composition of the neighborhood does not appear to directly affect the mortgage lending decision, but the race of the applicant does. The exact interpretation of the positive coefficient on the race variable, however, is debatable. Three alternative explanations are possible. Omitted variables may still exist that are positively correlated with both race and the probability

12. When the continuous measure of the racial composition of the tract is included in the regression without the denied PMI variable, it is statistically significant. When observations that were rejected by PMI are removed from the sample, the coefficient on the continuous neighborhood racial composition variable becomes insignificant.

13. Still another alternative specification, including both a dummy variable for applications that sought PMI and a variable that interacts the loan-to-value ratio with this dummy variable, also finds no direct redlining in the mortgage lending decision.

that a loan will be denied. Alternatively, statistical discrimination, where race is an effective proxy for loan profitability, may be the source of the significantly higher probability of mortgage denial for minorities. And finally, the coefficient on race could be capturing the effects of discrimination based on race that are uncorrelated with the profitability of the application.[14]

A closer examination of this data set finds little support for the conclusion that important variables have been omitted or that statistical discrimination is occurring. The purpose of the study was to include any variable that is systematically in the lenders' information set, and there is strong evidence that this goal was accomplished. Further, although the data in this paper were not designed to examine whether statistical discrimination is occurring, what information they do contain concerning this issue does not justify the conclusion that race's use as a signal of a higher conditional default probability explains the size and significance of its role in the mortgage lending decision.

A. *Omitted Variable Bias*

Studies of mortgage lending have been rife with complaints of omitted variable bias. Previous research, and any analysis using only the raw HMDA data, certainly suffer from this problem. The Boston Fed attempted to reproduce the information set of the lender in order to assess the role of race in the mortgage lending process. Accordingly, every variable on the standard loan form, as well as important information from the credit reports and the property appraisal, was collected. Many loan officers and underwriters in the Boston area were consulted to ensure that no variables important to the mortgage lending decision had been omitted from the survey, and every variable they mentioned as important was collected. Furthermore, all the information systematically provided to any secondary market buyer of the loan is in the data set collected for this study. Omitted idiosyncratic variables correlated with race could still exist, but in order for the omission of such variables to have a large effect on the estimate of the coefficient on race, they must be correlated with race even after accounting for all the other variables in this study. For ex-

14. Note that even if statistical discrimination is possible, its cost might be prohibitive because of the possibility of legal recourse. If these punitive costs are, in fact, prohibitive, the lenders would not choose to discriminate. In that case, the coefficient on race in the denial equation would be zero, even if minorities did have a higher conditional probability of defaulting.

ample, idiosyncratic variables may be correlated with income, location, educational attainment, and so forth, which are also correlated with race, but race remains important in the mortgage lending decision even after including all these other variables in the analysis. Whether an important factor has been omitted is always difficult to disprove. However, the prima facie case for an important omitted variable is not compelling.

It is possible that any important omitted variables would affect the estimation of the coefficients of other variables collected in the extended survey. Omitted variables correlated with race might also be correlated with other individual characteristics. For example, education in and of itself has no clear relationship to the probability of default, although it could be positively correlated with omitted variables, such as future income, that do affect the mortgage lending decision. If the effect of future income was not being captured by the variables in the base model, this correlation would produce a significant coefficient on education in the full model.

Table X examines this hypothesis for a collection of other individual characteristics that might be related to possible omitted variables but not intrinsically important to the mortgage lending decision. The first column presents the coefficient estimates and *t*-statistics for these other personal characteristics in a regression of mortgage denial on just these variables and race. The coefficients on the applicant's marital status, race, and whether the applicant had schooling beyond college were all significant beyond the 5 percent level, while the coefficients on the applicant's number of dependents and years on the current job are statistically significant at the 10 percent level. Higher education and being married significantly increase the probability of getting approved, while fewer years on the job and more dependents decrease it.

Once the other variables in the base regression are included in the estimation, column 2, only the borrower's marital status and race still significantly affect the decision to lend, even at the 10 percent level.[15] However, both these coefficients decline by the same order of magnitude. The final regression includes dummy variables for each tract as well. The inclusion of the tract variables tends to have little effect on any of the coefficient estimates

15. The significance of the marital status indicator variable is not robust to alternative specifications. As a result, it is omitted from the base model.

TABLE X
THE EFFECT OF OMITTED VARIABLES

Dependent variable = 1 if application is denied	Linear probability: Personal characteristics	Linear probability: Personal characteristics with base model	Linear probability: Personal characteristics with base model and tract dummies
Constant	0.09	−0.24	−0.34
	(5.82)	(−6.69)	(−3.88)
Education: less than high school	0.05	0.05	0.07
	(0.84)	(0.94)	(1.23)
Education: greater than college	−0.03	−0.02	−0.02
	(−2.44)	(−1.33)	(−1.48)
Female	−0.02	−0.01	−0.02
	(−0.92)	(−0.61)	(−1.20)
Age ≤ 25	0.04	0.04	0.04
	(1.56)	(1.88)	(1.78)
Years in current line of employment	0.0009	0.002	0.002
	(0.75)	(1.57)	(1.85)
Years in current job	−0.002	−0.001	−0.001
	(−1.80)	(−1.39)	(−1.02)
Single	0.05	0.03	0.02
	(2.96)	(2.03)	(1.23)
Number of dependents	0.01	0.003	0.006
	(1.82)	(0.44)	(0.91)
Race	0.17	0.08	0.08
	(8.69)	(4.40)	(3.26)
Adjusted R^2	0.05	0.30	0.30
Observations	2817	2817	2817

*t-statistics, adjusted for heteroskedasticity and for grouped errors at the tract level, are in parentheses.

for these personal characteristics. Yet now, of all these personal characteristics that could be correlated with omitted variables, only race remains significant in the lending decision. Clearly, omitting these control variables biases upward the coefficient estimates of all the personal characteristics, including race. Yet that race alone, among these characteristics remains statistically significant once these other control variables are included in the analysis suggests that it is affected less. The insignificance in the base model of these other individual characteristics with no clear relationship to the mortgage lending decision suggests that no important factors correlated with these individual traits have been omitted. Inclusion of these control variables does lessen the effect of race; the real issue is whether other such variables are still being omitted.

There appears to be little evidence that important variables systematically related to the mortgage lending decision have been omitted. Further examination of omitted variable bias requires specification of exactly which variables important to the decision are missing, proof that the lenders collect this information, and evidence that these variables are correlated with the race of mortgage applicants.

B. Statistical Discrimination

Statistical discrimination occurs when the base probability of default of one identifiable group is greater than that of another. The higher default probability is not necessarily related to economic fundamentals but is simply a statistical relationship. If the default rate for minorities, holding all else in the lender's information set constant, is higher than the rate for whites, statistical discrimination could produce a significant race coefficient in the denial equation. If statistical discrimination were occurring, the default probability of the marginal application for whites and for minorities should be equal, and the coefficient on race in the fully specified denial equation should be positive and statistically significant. It is often argued, conversely, that if the race coefficient in the denial equation is significant owing to taste-based discrimination, then the minority default rate should be lower as, on average, higher-quality minority applicants would be selected.[16]

However, Tootell [1993, 1995a] and Yinger [1993] show how examining the average default rates fails to prove whether any discrimination that might be occurring is statistical or taste-based. Firms lend at the margin, while accepted applications vary over a spectrum of denial probabilities. It is possible that the marginal minority loan that qualifies for a mortgage is of higher quality than the marginal white loan that qualifies, yet the average creditworthiness of the accepted minorities is lower than that of the accepted whites. If the distribution of minorities is skewed toward weaker applications, then more of their accepted applications will be near the potentially higher threshold for marginally acceptable minority loans. Tables II and III reveal that, in fact,

16. The minority default rate need not be lower under some models of taste-based discrimination. For example, if discrimination does not take the rational form of requiring stronger applications from minorities, the sign of the coefficient on race in a default regression would be uncertain.

on average minority applications are slightly weaker, even for accepted loans. Yet it is whether, at the margin, a white loan is accepted and a similar minority loan is denied that determines whether taste-based discrimination is occurring, not a comparison of the average qualifications of accepted applications.

In fact, default studies have not shown conclusively that the conditional probability of default for minorities is higher than that for whites. Some findings, as in Van Order, Weston, and Zorn [1993] and Berkovec, Canner, Gabriel, and Hannan [1994] suggest that minorities are just as likely or more likely to default, as would be consistent with a finding justifying statistical discrimination.[17] However, these studies omit variables such as credit history, which are positively correlated with race and rejection. This biases upward the estimation of the conditional default probability of minorities, and makes it difficult to interpret the results from these studies.[18]

Finally, attempting to account for possible statistical discrimination with these data did not affect the results. Using the applicant's credit history as the dependent variable, the applicant's probability of defaulting on other forms of debt was calculated as a function of race, net wealth, years on the job, and other personal and financial characteristics available to the lender.[19] The predicted default probabilities were then included in the equation explaining mortgage denials. Since race was significant in the first-stage regression, every minority applicant was expected to have a higher probability of mortgage default in this specification. Generalizing the higher default propensities to minorities who do not themselves have a record of a default reduces somewhat the importance of race, but it still does not eliminate

17. Even a finding that, all else held constant, minorities have a higher probability of defaulting on a loan says little about whether discrimination is occurring at the margin, however. See Tootell [1993, 1995a] and Yinger [1993].

18. It is also unclear whether the conditional default propensities from different loan characteristics are known by the lender. If lenders did not know the conditional default propensity, they would have no information that would motivate statistical discrimination.

19. There are several problems with modeling the probability of default in this way. The data from the mortgage-lending survey are not ideal for uncovering the determinants of consumer defaults because the determinants of consumer defaults may differ from those of mortgage defaults. Furthermore, the mortgage lending decision is forward-looking, not backward-looking. Looking backward at credit history also raises questions of timing. It is unclear whether the right-hand-side variables were valid at the time of, or before, the credit history blemish occurred. For example, a consumer default may have occurred when the applicant was a student. In that case, the education variable used in these first-stage regressions would be too large.

the effect of minority status on the mortgage lending decision. As a result, any basis for statistical discrimination found in this data set still does not explain the significant coefficient for race in the denial equation.

Although these data are not sufficient to distinguish perfectly between taste-based discrimination and statistical discrimination, what tests can be performed with this data set suggest that statistical discrimination is not the explanation for the significance of the race coefficient. The evidence here indicates that the correlation between race and the consumer delinquency probabilities does not explain the coefficient on race in the denial regression. Current studies of mortgage default data are also inadequate to provide clear evidence on whether race is correlated with defaults. In any event, however relevant this debate is for theory, whether statistical discrimination, taste-based discrimination, or both are occurring is irrelevant to issues of enforcement, since they are both illegal.

VI. Conclusion

It is usually difficult to unravel the possible effect of race from the possible effect of the racial composition of the neighborhood. In Boston these two forces can be identified since over 50 percent of the minority applicants applied for mortgages on properties in predominantly white areas. The extended HMDA data show that lenders do not appear to be redlining neighborhoods based on the racial composition of the tract, the average income in the area, or a variety of other neighborhood characteristics. There is some evidence that redlining is occurring in the lender's decision to require PMI. However, the evidence of discrimination in Boston strongly points to a reluctance of lenders to make loans to minorities wherever they apply, and not to a reluctance of lenders to extend credit in poor areas that happen to be minority.

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