Accepted in Journal of Urban Economics, 2002

University of Connecticut

Department of Economics Working Paper Series

Redlining, the Community Reinvestment Act, and Private Mortgage Insurance

Stephen L. Ross
University of Connecticut

Geoffrey M. B. Tootell
Federal Reserve Bank of Boston

Working Paper 2000-04

2000

341 Mansfield Road, Unit 1063
Storrs, CT 06269–1063
Phone: (860) 486–3022
Fax: (860) 486–4463
http://www.econ.uconn.edu/

Abstract

This paper examines whether neighborhood racial or income composition influences a lender's treatment of mortgage applications. Recent studies have found little evidence of differential treatment based on either the racial or income composition of the neighborhood, once the specification accounts for neighborhood risk factors. This paper suggests that lenders may favor applicants from CRA-protected neighborhoods if they obtain Private Mortgage Insurance (PMI) and that this behavior may mask lender redlining of low income and minority neighborhoods. For loan applicants who are not covered by PMI, this paper finds strong evidence that applications for units in low-income neighborhoods are less likely to be approved, and some evidence that applications for units in minority neighborhoods are less likey to be approved, regardless of the race of the applicant. This pattern is not visible in earlier studies because lenders appear to treat applications from these neighborhoods more favorably when the applicant obtains PMI.

Journal of Economic Literature Classification: R38, G12, G28, J71

Keywords: Community Reinvestment Act, Private Mortgage Insurance, Mortgage Lending, Discrimination

I. Introduction

The federal government has expressed a strong interest in assuring that potential homebuyers in minority and low-income neighborhoods have full access to credit. Process-based redlining in the mortgage industry is defined as the refusal to approve creditworthy loan applications for housing units in minority or in low-income neighborhoods. [1] This behavior, which constitutes discrimination against a neighborhood as opposed to discrimination against members of a racial or ethnic group, may depress property values in these vulnerable neighborhoods limiting the ability of minority and low-income households to accumulate wealth. Such underwriting policies also may restrict homeownership rates for minority and low-income households who predominantly reside in those neighborhoods.

The Community Reinvestment Act (CRA) of 1977 was passed to mitigate the problem of redlining and to addressed the perceived under provision of credit to low-income and minority neighborhoods. The CRA is a law that requires action, as opposed to a prohibiting behavior. Rather than simply outlawing redlining, the CRA requires federal financial supervisory agencies to use their authority to encourage financial institutions to help meet the credit needs of local communities.[2] Based on this requirement, these agencies evaluate the geographic distribution of mortgages issued by such institutions prior to approving bank charters, new branches, or mergers, but do not explicitly assess whether lenders discriminate against credit applications based on location.[3]

Current research indicates that the aggregate pattern of lending in many cities is consistent with redlining based on race,[4] but direct studies of the mortgage application approval process tend to find little evidence of redlining by neighborhood racial composition or income distribution.[5] Schafer and Ladd [16] examine approximately 20 metropolitan areas in New York and California and have mixed results, finding evidence of racial or ethnic redlining in some locations but no evidence in many others. Schill and Wachter [17] examine applications in Boston and Philadelphia and find no evidence of redlining by neighborhood racial or income composition after controlling for neighborhood risk variables. Similarly, the only study of redlining that controls for both applicant credit history and neighborhood risk, Tootell [22], finds no evidence of racial or income redlining in Boston.[6]

Existing studies may have missed evidence of redlining because they do not consider ways in which lenders may respond to the Community Reinvestment Act (CRA). Lenders may be hesitant to underwrite mortgages in minority or low-income neighborhoods because of a real or perceived higher default risk from loans issued in such neighborhoods, but lenders also face governmental pressure to issue mortgages in low-income and minority neighborhoods because of the Community Reinvestment Act (CRA). Moreover, the CRA does not create any pressure for lenders to treat applications from high-income and low-income neighborhoods the same, but only to increase their overall lending in low-income neighborhoods.

Private Mortgage Insurance (PMI) may provide lenders with an opportunity increase lending in low-income and minority neighborhoods in order to meet their CRA obligations while avoiding at least part of the associated increase in underwriting risk. PMI is purchased by the borrower and provides protection for the lender from losses associated with a mortgage default by covering a certain percentage of the total mortgage amount. The borrower submits a PMI application during the application stage of the mortgage process, and a final underwriting decision is usually not made until the result of the PMI application process is known. Since the CRA makes no provision for equal treatment among mortgage applications, lenders have an incentive to deny potentially risky applications from low-income or minority neighborhoods when they are exposed to the entire risk of loss from default and to meet their CRA obligations by approving these applications when they are insulated from part of the loss by the presence of PMI.

The paper estimates a model of mortgage application denial in which the influence of neighborhood racial and/or income composition varies by whether the applicant obtains PMI using data from the 1990 HMDA sample developed by the Federal Reserve Bank of Boston and used in Munnell, Tootell, Browne, and McEneany [13]. Strong evidence is found to suggest that mortgage applications from low-income and/or minority neighborhoods without PMI are more likely to be denied when compared to equivalent applications from other neighborhoods and that applications from low-income and/or minority neighborhoods with PMI are less likely to be denied when compared to applications without PMI from similar neighborhoods. The strongest evidence is for redlining against low-income neighborhoods. The tract income results persist in a model that controls for both tract income and racial composition using thresholds that are consistent with the Community Reinvestment Act. Moreover, some evidence is found to suggest that mortgage applications from low-income neighborhoods with PMI are treated favorably compared to applications from medium to high-income neighborhoods.

II. Data and Model Specification

This study uses the sample of 1990 HMDA loan applications used in Munnell, Tootell, Browne, and McEneaney [13] and Tootell [22, 23].[7] This sample contains 2,925 applications, of which 344 and 335 were for properties located in minority and low-income neighborhoods, respectively. The dependent variable is binary and takes the value of one in the case where the loan application was denied. The model specification is based on the expanded model used in Munnell et al, which results in a loss of an additional 87 observations that have missing information on one or more of those variables.[8] A new variable is created that takes on a value of one if the loan applicant obtained PMI and zero otherwise, and all observations in which an application for PMI was denied are dropped from the sample leading to the loss of an additional 75 observations.[9] The final sample contains 2,763 applications. A complete list of variables used in the specification, along with their means and standard deviations, are provided in Table 1.

The analysis includes many variables that represent the risk of default for an applicant, such as the applicant's credit history,[10] household debt burdens, and the ratio of the loan amount to the minimum of the appraised value and house price.[11] The specification also contains several proxies meant to capture the risk of suffering spells of unemployment. These include whether the applicant is self-employed and the unemployment rate of workers in the applicant's industry. Other individual characteristics, such as education, job tenure and experience, age, marital status, gender, and number of dependents, add further controls for the unemployment risk. Property characteristics, such as whether the loan was for a multifamily property or whether the unit was owner-occupied, are included as well.[12] Finally, the specification controls for detailed loan and borrower characteristics. The loan variables include whether a gift was provided for the downpayment, whether the loan was cosigned, whether the interest rate was adjustable,[13] and whether private mortgage insurance was obtained.

Lenders may approve fewer applications from low-income or minority neighborhoods because they are legitimately responding to neighborhood variables that explain default risk. In order to control for neighborhood risk factors, additional variables found in the U.S. Census are included in the specification. These variables include the boarded-up rate and the vacancy rate,[14] as well as a measure of the riskiness of asset prices in that neighborhood, the rent-to-value ratio. The rent-to-value ratio is the ratio of median rental payments to the median value of the rental stock within a tract based on U.S. Census data. A high ratio implies that investors do not expect the current stream of rental payments to persist over time and suggest that the properties in those tracts may face increased equity risk. This future risk will be capitalized into the value of properties, but not into the current rental price.

The variables intended to capture racial or income-based redlining are also based on census data. The specification includes a dummy variable for whether the minority population share in the tract exceeds 30 percent, as was used in Tootell [22]. Alternative definitions of a minority neighborhood were examined, but changing the threshold had little effect on the results.[15] The tract income variable is defined as a dummy variable equal to one when tract median income is below $32,000, which is one standard deviation below the metropolitan area mean for tract median income. A low-income threshold was chosen because such a threshold seems most appropriate for an analysis of CRA and redlining. The enforcement of CRA is conducted by examining the flow of credit to low-income and predominantly minority neighborhoods where the definition of a low-income or minority neighborhood is specific to the region or metropolitan area in which the lender is operating.

For both neighborhood income and racial composition, the tract variable is included directly in the specification, as well as being interacted with a dummy variable for PMI obtained. The coefficient on the tract variable itself tests for redlining against applications in which the borrower did not apply for PMI, and the coefficients on the interactions test for whether redlining varies with PMI status.[16] The paper also presents significance tests for whether the sum of these two coefficients differs from zero, which compares the treatment of applications with PMI from a minority or low-income neighborhood to the treatment of similar applications from predominantly white, medium to high-income neighborhoods. Two specifications are estimated and presented; one includes borrower, loan, and property characteristics, while a second adds tract risk variables. All models estimated follow a probit specification, and all standard errors are corrected for heteroscedasticity across census tracts, see Huber [10] and White [24].

Race-Based versus Income-Based Redlining

Lenders may redline along either racial or income composition of the neighborhood. This complicates tests for redlining, because these variables may be highly correlated. For example, in the Boston sample, dummy variables for whether a census tract is more than 30 percent minority and for whether the median tract income is one standard deviation below the metropolitan area median have a correlation coefficient of 0.71. Therefore, the paper examines the relationship between loan denial and tract racial or income composition in stages. The first set of estimates controls for tract racial composition, but does not include any controls for tract income. The second set controls for tract income, but does not control for racial composition.

Specifications that include both tract income and racial composition may have low power for detecting redlining owing to the high correlation between the two tract variables. The high correlation may arise from the specific thresholds chosen for this analysis. For this reason, we examine the effects of "low-income" tracts as defined by three different thresholds. In fact, if the income threshold rises to our medium threshold, the correlation between the two variables falls to 0.57. If the threshold rises to our high threshold, the correlation falls to 0.43. Three additional specifications are estimated that include both the tract racial composition variable and one of the tract "low-income" variables: either low threshold, medium threshold, or high threshold.

PMI and Loan-to-Value Ratio

The controls for the loan-to-value ratio (LTV) are especially relevant to a study of PMI. The most common use of PMI is to compensate for a downpayment amount of less than 20% of the property's assessed value (LTV above 0.8) by providing sufficient insurance coverage so that sum of the downpayment and the PMI coverage equals 20%. In general, the major Government Sponsored Enterprises (GSE's) that purchase mortgages on the secondary market, FreddieMac and FannieMae, will not purchase mortgages with a downpayment of less than 20% unless such coverage is obtained. In addition, GSE's cannot purchase mortgages with downpayments that are less than 5% of assessed value. Therefore, mortgage applicants typically apply for PMI when the LTV is between 0.80 and 0.95.

If borrowers and underwriters never departed from these secondary market guidelines, the effect of a PMI application on loan approval would not be identified separately from the LTV coefficients. Therefore, the coefficients on the PMI variables are identified by applications from borrowers that depart from these general guidelines. In fact, these guidelines were regularly violated in the Boston mortgage market of the early 1990s. Table 2 categorizes applications by LTV and whether the borrower applied for PMI. As expected, of the 1581 applications with LTVs at 0.80 or below, only 61 applied for PMI, while the percentage of applications where PMI was sought increased dramatically when LTV was above 0.80. However, only 548 of the 1088 applicants with LTVs between 0.80 and 0.95 actually sought PMI. In addition, almost half of the applicants with LTVs above 0.95 sought PMI, even though PMI companies usually are unwilling to cover loans with very high LTVs.

These apparent discrepancies can be explained if the relationship between LTV and PMI is based on general guidelines rather than hard and fast rules. In rare cases, applications with LTVs below 0.80 are denied because the applicant or loan application has other negative characteristics, such as poor credit history. Under those circumstances, a borrower with a low LTV, but a high likelihood of loan denial, might apply for PMI. Similarly, borrowers with high LTVs, but otherwise high-quality loan applications, may refuse to apply for PMI. A lender may choose to hold such a loan in its own portfolio and self insure, rather than lose the business.

Table 3 categorizes loans by LTV, by whether PMI was obtained, and by whether the loan was sold on the secondary market. As expected, when the LTV is above 0.80, the majority of loans not covered by PMI are held in the lender's portfolio, and the majority of covered loans are sold on the secondary market. This relationship between PMI and resale is even stronger for loans with LTVs above 0.95. Admittedly, some high-LTV loans without PMI are sold on the secondary market, but it is important to remember that there are also private secondary market players who are not governed by the same safety and soundness regulations as the GSE’s. In fact, the role of private secondary market purchasers is illustrated by the sale of 95 mortgages with LTV's above 0.95, which the GSE's are not allowed to purchase.[17]

A similar issue arises with the receipt of PMI for very high LTV loans. Of the 118 applications that applied for PMI with LTVs above 0.95, Table 3 shows that 95 received approval for PMI. This result should not be surprising. Almost all of these applications had loan-to-value ratios only 1 or 2 percentage points above the 95 percent level. Further, PMI companies operating in the Boston area at the time did grant insurance to applications with loan-to-value ratios above 95 percent at a higher premium. Finally, loan applicants are unlikely to apply for PMI unless they stand a reasonable chance of receiving coverage.

In spite of these explanations, there is still concern that the coefficients on the PMI variables might be identified based on applications that are different in some way, because the treatment of these applications violates the general guidelines. Moreover, these concerns may raise issues regarding the relevance of the findings to today's mortgage market especially given the growth of the secondary mortgage market and the expanded use of automated underwriting models, which both tend to move the overall market towards more uniform rules and guidelines. In terms of relevance, much of the secondary market growth during the 1990's was associated with new private purchasers who as discussed earlier are not subject to the same regulations as the GSE's.

Finally, this issue really involves the econometric identification of the behavior as opposed to the existence of the phenomenon. Lenders might still favor mortgage applications from minority tracts with PMI, but the coefficients intended to capture this effect would not be identified. In order to address this concern, the loan denial specification is re-estimated using the sample of applications in which the borrower did not apply for PMI. As above, the coefficient on the tract variable provides a test for redlining against applications in which the borrower did not obtain PMI, and the specification does not require the estimation of any PMI parameters.

Lenders that Operate in a Diverse set of Neighborhood

This sample contains mortgage applications submitted to a diverse sample of lenders. An observed relationship between neighborhood and the influence of PMI on application denial may arise because lenders vary in both their likelihood of requiring PMI and in the geographic composition of their market. For example, if lenders with stringent underwriting standards draw applications primarily from white neighborhoods and tend not to require PMI, minority applications with PMI will tend to face weaker underwriting standards on average and be approved more frequently. See Ross and Yinger [13] for a detailed analysis of lender variation in underwriting standards using the same sample of applications.

Two approaches are used to address this issue. First, applications to lenders that do not appear to do business in low-income neighborhoods are dropped from the sample. Specifically, two subsamples are created: one eliminating all applications to lenders who did not receive a mortgage application to purchase housing in a low-income neighborhood, and a second eliminating all applications to lenders who did not approve a mortgage application to purchase housing in a low-income neighborhood. The resulting subsamples contained 1969 and 1929, respectively. The second approach analyzes the entire sample using a specification that includes lender dummy variables in order to control for lender differences in the stringency of underwriting standards.

The Link between PMI and Neighborhood Risk

An analysis of the role of neighborhood racial composition and income in underwriting requires controls for neighborhood equity risk. Tootell [22] and Schill and Wachter [17] document the importance of neighborhood risk in underwriting, and this paper follows Tootell

[23] by controlling for the rent-to-value ratio in the neighborhood. If lenders consider PMI when evaluating the importance of equity risk, the influence of PMI may vary with rent-to-value ratio biasing our estimation results. Therefore, additional estimations are conducted in which rent-to-value ratio is interacted with whether PMI was obtained.[18]

Endogeneity Bias and PMI

A final concern is that the decision to apply for PMI may be endogenous to the underwriting process. This endogeneity may arise through two possible channels. First, some unobserved borrower characteristics may influence a borrower's willingness to accept PMI and also may be used by the lender in the underwriting process. Unobserved characteristics that imply that the borrower is more creditworthy may also encourage the borrower to refuse to apply for PMI. Alternatively, unobserved lender characteristics may influence lender underwriting standards and affect the circumstances under which a lender will require a borrower to apply for PMI.

If the PMI variables are endogenous, the resulting simultaneous process is quite complex. The process actually involves three discrete choices: the decision to apply for PMI, the PMI company's decision concerning each PMI application, and finally the lender's underwriting decision for each application.[19] Furthermore, the interactions between tract characteristics and PMI status require a complex simultaneous equations specification, which is not necessarily identified.

However, a simple framework is available because the attention of this paper is focused on whether or not the borrower obtained PMI. Specifically, obtaining PMI and loan denial are estimated simultaneously using a bivariate probit in which the endogenous PMI variable recursively influences the latent variable in the denial equations. The influence of the endogenous PMI variable is allowed to vary by the race of the applicant and by the income and racial composition of the tract, which provides an additional test of the paper's fundamental hypothesis. The influence of PMI being obtained on denial is identified without imposing traditional exclusion restrictions because PMI obtained is a limited dependent variable, see Sickles and Schmidt [21] and Amemiya [1].[20]

III. Estimation Results

Table 4 presents estimations that are comparable to those of Tootell [22] including detailed loan, borrower, unit, and neighborhood characteristics as well as the new PMI obtained variable. The first estimation contains the minority tract dummy variable, the second contains the low-income dummy variable, and the third contains both variables. These estimations provide only weak evidence of racial redlining by tract racial composition. The coefficient on racial composition is only significant at the 90% confidence level in the estimation that controls for racial composition only and insignificant in the specification that controls for both neighborhood race and income. The last two columns provide some evidence that the probability of loan denial falls with tract income. The coefficient on neighborhood income is statistically significant in the first specification, but only significant at the 90% level in the model that controls for both neighborhood race and income.[21]

Tract Racial and Income Composition Separately

As discussed earlier, the correlation between the variables for tract income and the racial composition of the tract is very high, and the estimation results may be quite sensitive to whether these variables are examined separately or jointly. Table 5 columns 1 and 2 present estimations for models that exclude the tract income variable and control for the effect of applying for PMI by including interactive terms between PMI acceptance and denial with race and the racial composition of the tract. In these specifications, the coefficient on the minority tract variable is positive and always statistically significant. Applications for mortgages on units in minority neighborhoods are more likely to be denied. This finding is consistent with redlining by racial composition against borrowers who do not apply for PMI.

Furthermore, the coefficient on the interaction of the minority tract variable and the accepted for PMI variable is negative. Application for and receipt of PMI increases the likelihood of approval for all applications. There is also, however, an additional negative effect on the denial probability for mortgage applications on units located in minority neighborhoods. This result is consistent with the hypothesis that lenders favor minority neighborhood mortgage applications with PMI as a low-risk option for responding to the CRA requirements.

Table 5 columns 3 and 4 estimates comparable specifications where the minority tract variable is replaced with a dummy variable for whether the tract has a low median income. The results are the same. Applications for units in low-income tracts are less likely to be approved, and the application for and receipt of PMI has a larger effect on the approval likelihood for applications on units located in low-income neighborhoods. The findings in Table 5 provide strong, direct evidence that lenders redline, either by tract race or income, when a borrower does not apply for PMI. The findings also provide indirect evidence that the CRA has a positive impact on credit access in either minority or low-income neighborhoods, but that this increased access is at least partially paid for by increased expenditures on PMI.

These results are based on the comparison of applications in minority or low-income tracts with PMI to applications in minority and low-income tracts without PMI after pulling out the direct effect of PMI. An alternative question is whether applications with PMI in minority or low-income tracts are actually treated favorably relative to applications with PMI in predominantly white, medium to high-income tracts. This hypothesis involves the sum of the tract variable and the interaction between the tract variable and whether PMI was obtained. The interaction coefficients are substantially larger (over double) than the direct effect of low income or minority tract. The sum of these coefficients, however, are not statistically significant for the minority tract estimates, and significant at the 95% and 90% level of confidence for the low-income tract estimates without and with additional tract controls, respectively. The sample cannot completely distinguish between a situation in which loans with PMI are simply not discriminated against and a situation in which they are favored over loans in white neighborhoods. In either case, however, the lender is able to improve their CRA numbers relative to a world in which the influence of neighborhood on underwriting does not vary by PMI.[22]

These results are also consistent with Tootell's [22] observations concerning PMI. Tootell suggests that applicants for housing units in minority tracts may be forced to apply for PMI. Beyond suggesting PMI for applications in minority tracts, a lender's only leverage is in the loan denial decision. The results in this paper can be interpreted as showing that lenders force applicants to apply for PMI when the units are in minority tracts, by rejecting those applications if the applicant does not apply for PMI. While Tootell's findings indirectly suggest such behavior, this study finds evidence based directly on the adverse treatment of applicants who do not apply for PMI.

Tract Racial and Income Composition Combined

Table 6 presents re-estimations of the specifications from Table 5 columns 2 and 4 including both the minority and income tract variables as well as the interaction of these tract variables with PMI status. The first specification is based on the low-income threshold. The results of this estimation are consistent with redlining by tract income and with a positive PMI effect for tract income as well. Specifically, the results for redlining based on tract income when the borrower has not obtained PMI are robust to controlling for tract racial composition, but the results for tract racial composition are not robust. This threshold seems most relevant for considering the effect of CRA on underwriting, and the findings do not provide evidence of redlining based on the racial composition of the neighborhood.

When the threshold defining a low-income neighborhood is raised, the second two specifications in Table 6, the results are consistent with redlining by tract racial composition, and no evidence of redlining by tract income is found. Evidence of redlining by race reappears when the specification includes a tract income measure that is less highly correlated with race. This study cannot distinguish, however, between a situation in which racial redlining is masked by this high correlation and a situation in which redlining only occurs against low-income neighborhoods. The positive effect of PMI on loan approval still arises, however, based on tract income. The evidence points to the fact that CRA has improved credit access based on neighborhood income rather than neighborhood racial composition.[23]

These findings consistently support the notion that CRA has increased access to credit for low- and moderate-income neighborhoods when borrowers obtain PMI. For mortgage applications in which the borrower does not apply for PMI, lenders appear to practice redlining by either tract income or racial composition depending upon the threshold used to defined low-income tract. In our opinion, the low threshold for low-income tract (one standard deviation below metropolitan area median income) is the most relevant threshold for analyzing the CRA. Using this threshold, the evidence points towards redlining based on neighborhood income rather than racial composition.

The Subsample of Those Who Did not apply for PMI

Table 7 presents re-estimations of the models in Table 8, except that the estimations are based on the subsample of applications in which borrowers did not apply for PMI. As a result, all PMI variables are dropped from the specification. The key findings in Table 6 are robust. For a low-income threshold, lender redlining appears to be driven by tract income. However, when the threshold is raised, lender redlining appears to be driven by tract racial composition.

Controlling for Lender Diversity

Table 8 presents the results for two alternative samples and one alternative specification using the low threshold for defining low-income tract. The first two columns present results for a subsample of applications to lenders who received applications for housing in low-income tracts and who actually approved applications for housing in low-income tracts. The third column presents the estimation results for a model that includes lender dummy variables. Neither the elimination of lenders who do not appear to serve low-income tracts nor the addition of controls for lender differences in underwriting standards affect the basic findings.

Does the Influence of PMI vary by Tract Risk

Table 9 presents the results for a model that includes the interaction between rent-to-value ratio and whether PMI was obtained. These interactions are statistically insignificant for all three thresholds used to define a low-income tract. The basic findings are robust. Redlining against low-income tracts is found when a low threshold is used, and redlining against minority tracts is found when higher thresholds are used. In addition, the favoring of applications from low-income neighborhoods with PMI arises for all tract income thresholds, but for the highest threshold the estimated coefficient is only significant at the 90% level of confidence.

Modeling Whether an Applicant Obtained PMI

Lastly, the denial model for the low threshold for low-income tract in Table 6 is re-estimated simultaneously with a model for whether the applicant obtained PMI, using a bivariate probit in which the endogenous PMI variable recursively influences the latent variable in the denial equation. Table 10 contains the results of these estimations. The correlation is small, -0.14, and not significantly different from zero, with a t-statistic of only -0.49. This estimation procedure provides no evidence that PMI is endogenous to the underwriting process. After controlling for the endogeneity of the PMI decision, loan applications in which the borrower did not apply for PMI were more likely to be denied when the application was from a unit in a low-income tract, and applications for a unit in a low-income tract were treated more favorably when PMI was obtained by the applicant.

Summary and Conclusions

This paper reexamines the question of whether lenders adversely treat mortgage applicants who purchase housing units in minority or low-income neighborhoods (redlining). Schill and Wachter [18] and Tootell [22] found no direct evidence of racial- or income- based redlining after controlling for neighborhood risk factors in the underwriting process. This finding is reversed after controlling for the influence of private mortgage insurance (PMI). Mortgage applications are more likely to be denied when the housing unit is in a low-income neighborhood if the applicant does not apply for PMI. This study supports the notion offered in Tootell [22] that mortgage applicants are forced to apply for PMI when the housing units are in low-income tracts. Applicants for units in low-income neighborhoods may feel compelled to apply for PMI because of the high loan denial rates in these neighborhoods when applicants do not apply for PMI.

Existing studies may have missed evidence of redlining because they do not consider ways in which lenders may respond to the Community Reinvestment Act (CRA). If lenders are concerned about default risk in minority neighborhoods, they have an incentive to meet their CRA obligations by approving applications in low-income neighborhoods when those applications are covered by PMI. This approach gives lenders more flexibility when choosing whether to approve uninsured loans in low-income neighborhoods. This type of behavior increases the cost of credit for home buyers in low-income neighborhoods and may work against the goals of the CRA. Given this possibility, agencies responsible for enforcing the CRA should focus more closely on the portions of lenders' portfolios that are not covered by PMI.

On the other hand, this study does suggest that CRA has increased access to credit in low-income neighborhoods. Strong evidence is presented that mortgage applications with PMI and in low-income tracts are less likely to be denied than applications without PMI in those tracts even after controlling for the direct effect of PMI. Some evidence also suggests that the applications with PMI from low-income neighborhoods are actually treated as favorably compared to applications with PMI from medium and high-income tracts. Lenders may be responding to CRA by favoring low-income tracts once PMI has been received, and this effect counteracts the high denial rates for applications without PMI and in low-income tracts. While an implicit PMI requirement for mortgages in low-income neighborhoods may raise the cost of credit, such a situation is certainly to be preferred to a world in which credit is not available in those neighborhoods.

Because of limitations in the Boston sample, this analysis cannot definitively determine whether lenders redline against minority or low-income neighborhoods. However, this analysis finds a strong pattern of loan denials for loans on units in either type of tract when PMI is not present, and provides the first direct evidence based on a complete underwriting specification that some mortgage applications may have been denied based on the neighborhood characteristics that legally should not be considered in the underwriting process.

Finally, we have no way to assess the generalizability of these results to the mortgage market of the late 1990's and beyond. The market underwent many changes during the 1990's including increased use of automated underwriting, growth of the secondary market, and increased use of risk-based pricing. Automated underwriting and the growing importance of the secondary market probably led to increased standardization concerning the PMI requirement. Risk-based pricing may limit the use of neighborhood risk factors, such as racial composition or income, in underwriting, as well as limit the incentive to impose a PMI requirement based on neighborhood risk. Nonetheless, the issues raised by this paper are still very important in today's mortgage market. Standardization of the PMI requirement may lead lenders to consider other mortgage application attributes in order to limit exposure in low-income neighborhoods, and increased risk-based pricing may simply transfer redlining from the underwriting stage to the credit pricing stage of the transaction.

References

1. T. Amemiya, Multivariate regression and simultaneous equation models when the dependent variables are truncated normal, *Econometrica*, **42**, 999-1012 (1974).
2. R. B. Avery, P. E. Beeson, and M S. Sniderman, Accounting for Racial differences in housing credit markets, *in* "Mortgage Lending, Racial Discrimination, and Federal Policy" (J. Goering and R. Wienk, Eds.), Urban Institute Press, Washington, DC (1996).
3. R. B. Avery and T. M. Buynak, Mortgage redlining: Some new evidence, *Economic Review (Federal Reserve Bank of Cleveland*), **17**, Summer, 15-31 (1981).
4. D. G. Blanchflower, P. B. Levine, and D. J. Zimmerman, Discrimination in the small business credit market, National Bureau of Economic Research, Working Paper #6840 (1998).
5. K. L. Bradbury, K. E. Case, and C. R. Dunham, Geographic patterns of mortgage lending in Boston, 1982-1987, *New England Economic Review (Federal Reserve Bank of Boston)*, September/October, 3-30 (1989).
6. W. A. Brock and S. N. Durlauf, Discrete choice with social interactions, *Review of Economic Studies*, **68**, 253-260 (2001).
7. W. J. Boyes, D. L. Hofman, and S. A. Low, An econometric analysis of the bank credit scoring problem, *Journal of Econometrics*, **40**, 3-14 (1989).
8. K. Cavalluzzo and L. C. Cavalluzzo, Market structure and discrimination: The case of small businesses, *Journal of Money, Credit, and Banking*, **30**, 771-791 (1998).
9. A. Holmes and P. Horvitz, Mortgage redlining: Race, risk, and demand, Journal of Finance, **49**, 81-99 (1994).

10. P. J. Huber, The behavior of maximum likelihood estimates under non-standard conditions, *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1, 221-233 (1967).

11. W. Lang and L. Nakamura, The dynamics of credit markets in a model of learning*, Journal of Monetary Economics*, 26, 305-318 (1990).

12. W. Lang and L. Nakamura, A model of redlining, *Journal of Urban Economics*, 33, 223-234 (1993).

13. A.H. Munnell, G. M. B. Tootell, L. E. Browne, and J. McEneaney, Mortgage lending in Boston: Interpreting the HMDA data, *American Economic Review*, **86**, 25-53 (1996).

14. S. L. Ross and J. Yinger, "The Color of Credit: What is Known about Mortgage Lending Discrimination," MIT Press, Cambridge, MA (2002).

15. S. L. Ross and J. Yinger, Does discrimination exist? The Boston Fed study and its critics *in* "Mortgage Lending Discrimination: A Review of Existing Evidence" (M.A. Turner and F. Skidmore, Eds.), Urban Institute Monograph Series on Race and Discrimination, Washington, DC (1999).

16. R. Schafer and H. F. Ladd, "Discrimination in Mortgage Lending," MIT Press, Cambridge, MA (1981).

17. M. H. Schill and S. M. Wachter, Borrower and neighborhood racial and income characteristics and financial institution mortgage application screening, *Journal of Real Estate Finance and Economics*, 9, 223-240 (1994).

18. M. H. Schill and S. M. Wachter, A tale of two cities: Racial and ethnic geographic disparities in home mortgage lending in Boston and Philadelphia, *Journal of Housing Research*, 4, 245-276 (1993).

19. A. B. Shlay, Not in that neighborhood: The effects of population and housing on the distribution of mortgage finance within the Chicago SMSA, *Social Science Research*, **17**, 137-163 (1988).

20. A. B. Shlay, Financing community: Methods for assessing residential credit disparities, market barriers, and institutional reinvestment performance in the metropolis, *Journal of Urban Affairs*, **11**, 201-223 (1989).

21. R.C. Sickles and P. Schmidt, Simultaneous equation models with truncated dependent variables: A simultaneous Tobit model, *Journal of Economics and Business*, **32**, 11-21 (1978).

22. G. M. B. Tootell, Redlining in Boston: Do mortgage lenders discriminate against neighborhoods? *Quarterly Journal of Economics*, **111**, 1049-1079 (1996).

23. G. M. B. Tootell, Discrimination, redlining, and private mortgage insurance, unpublished manuscript (1996).

24. H. White, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica*, **48**, 817-830 (1980).

Table 1
Means of Variables

	Did Not Apply for PMI	PMI Obtained
Variable		
Application Denied	0.152 (0.361)	0.030 (0.168)
Ability to Support Loan		
Housing Expense/Income	0.216 (0.410)	0.179 (0.382)
Total Debt Payments/Income	0.331 (0.123)	0.331 (0.055)
Net Wealth (1000's)	0.301 (1.143)	0.052 (0.196)
Unemployment Region	3.84 (2.08)	3.72 (2.01)
Self employed	0.14 (0.35)	0.05 (0.22)
Consumer Credit History	2.18 (1.70)	2.08 (1.66)
Mortgage Credit History	1.70 (0.57)	1.87 (0.35)
Public Records	0.085 (0.279)	0.044 (0.206)
Loan/Appraised Value: Low[a]	0.356 (0.479)	0.025 (0.155)
Loan/Appraised: Medium	0.392 (0.488)	0.771 (0.420)
Loan/Appraised Value: High	0.063 (0.243)	0.163 (0.369)
Property Characteristics		
Two to four-family home	0.115 (0.319)	0.180 (0.381)
Not Owner occupied	0.050 (0.218)	0.003 (0.055)
Tract Characteristics		
Percent of minority in tract	0.080 (0.268)	0.220 (0.415)
Low Income Tract[b]	0.084 (0.278)	0.196 (0.398)
Boarded-up Rate (>1.2%)	0.034 (0.180)	0.080 (0.273)
Vacancy Rate (>4.6%)	0.055 (0.227)	0.070 (0.256)
Rent/Value in tract	0.090 (0.240)	0.100 (0.200)
Personal Characteristics		
Race	0.196 (0.397)	0.328 (0.470)
Age divided by 100	0.373 (0.100)	0.341 (0.081)
Female	0.203 (0.403)	0.227 (0.419)
Married	0.400 (0.491)	0.397 (0.490)
Number of dependents	0.790 (1.133)	0.731 (1.050)
High School educated	0.245 (0.430)	0.330 (0.470)

New Profession[c]	0.038 (0.191)	0.058 (0.234)
New Job	0.191 (0.390)	0.204 (0.403)

	Did Not Apply for PMI	PMI Obtained
Terms of Loan		
MHFA (Special loan Program)	0.030 (0.156)	0.179 (0.380)
Gift	0.142 (0.349)	0.278 (0.448)
Adjustable Loan Rate	0.370 (0.481)	0.229 (0.421)
Cosigner	0.035 (0.185)	0.040 (0.196)

[a] Low loan-to-value refers to values between 0.6 and 0.8. Medium refers to value between 0.8-0.95, and high loan-to-value refers to values greater than 0.95.

[b] Minority Tract refers to tracts with minority composition greater than 30%, and low income tract refers to tracts with median income below $32,000, which is one standard deviation below the median income of the Boston metropolitan area. Boarded-up rate =1 if boarded up rate in tract is greater than 1.2% and zero otherwise, and vacancy rate =1 if vacancy rate in tract is greater than 4.6% and zero otherwise, which are both based on one standard deviation above the median for the Boston metropolitan area.

[c] New job = 1 if number of years at job is less than 2 years and zero otherwise. New profession = 1 if number of years in present line of employment is less than 2 years and zero otherwise

Table 2
LTV and PMI

	Did not apply for PMI	Applied for PMI
LTV ≤ .8	1520	61
.8 < LTV≤ .95	540	548
LTV > .95	138	118

Table 3
LTV, PMI, and the Disposition of Mortgages

	Held in Portfolio	Sold on Secondary Market
LTV≤ .8		
No PMI	680	703
PMI	7	46
.8 < LTV≤ .95		
No PMI	252	146
PMI	168	317
LTV > .95		
No PMI	72	17
PMI	17	78

Table 4

Redlining

Loan Denial Models	Redlining by Racial Composition	Redlining by Income	Redlining by Income and Racial Composition
Constant	-3.761 (0.298)[a]	-3.738 (0.298)	-3.742 (0.298)
<u>Ability to Support Loan</u>			
Housing Expense/Income	0.201 (0.084)	0.212 (0.085)	0.208 (0.084)
Total Debt Payments/Income	2.756 (0.481)	2.765 (0.483)	2.762 (0.482)
Net Wealth	0.045 (0.022)	0.044 (0.023)	0.044 (0.023)
Unemployment Region	0.042 (0.019)	0.041 (0.019)	0.041 (0.019)
Self employed	0.219 (0.108)	0.229 (0.109)	0.227 (0.108)
Consumer Credit History	0.175 (0.019)	0.174 (0.020)	0.174 (0.020)
Mortgage Credit History	0.192 (0.067)	0.188 (0.067)	0.190 (0.067)
Public Record History	0.652 (0.108)	0.649 (0.109)	0.651 (0.109)
Loan / Appraised Value: Low	0.246 (0.137)	0.238 (0.137)	0.239 (0.137)
Loan/Appraised Value: Medium	0.494 (0.137)	0.477 (0.137)	0.477 (0.138)
Loan/Appraised Value: High	0.912 (0.171)	0.833 (0.171)	0.886 (0.171)
<u>Property Characteristics</u>			
Two-to-four family home	0.206 (0.099)	0.209 (0.099)	0.199 (0.100)

Not Owner Occupied	0.482 (0.173)	0.475 (0.174)	0.479 (0.174)

[a] Standard errors are shown in parentheses for all tables.

Loan Denial Models	Redlining by Racial Composition	Redlining by Income	Redlining by Income and Racial Composition
Tract Characteristics			
Minority Tract	0.244 (0.129)		0.112 (0.143)
Low Income tract		0.273 (0.112)	0.217 (0.127)
Boarded Up Rate	-0.040 (0.178)	-0.057 (0.177)	-0.087 (0.182)
Vacancy Rate	-0.082 (0.168)	-0.099 (0.169)	-0.099 (0.168)
Rent/Value in Tract	0.411 (0.097)	0.358 (0.080)	0.368 (0.080)
Personal Characteristics			
Race	0.338 (0.101)	0.359 (0.096)	0.341 (0.100)
Age	0.218 (0.459)	0.199 (0.459)	0.202 (0.459)
Female	-0.088 (0.099)	-0.092 (0.098)	-0.092 (0.098)
Married	0.147 (0.092)	0.145 (0.091)	0.143 (0.092)
Number of Dependents	0.013 (0.035)	0.009 (0.035)	0.009 (0.035)
High School Educated	0.078 (0.092)	0.082 (0.091)	0.080 (0.092)
New Profession	0.037 (0.097)	0.049 (0.097)	0.048 (0.097)

New Job	-0.269 (0.236)	-0.293 (0.237)	-0.287 (0.236)

[a] Standard errors are shown in parentheses for all tables.

Loan Denial Models	Redlining by Racial Composition	Redlining by Income	Redlining by Income and Racial Composition
Terms of Loan			
MHFA	0.095 (0.157)	0.078 (0.158)	0.070 (0.158)
Gift	-0.034 (0.105)	-0.035 (0.105)	-0.035 (0.105)
Adjustable Rate Loan	-0.264 (0.085)	-0.265 (0.085)	-0.264 (0.085)
Cosigner	-0.252 (0.204)	-0.259 (0.204)	-0.254 (0.205)
PMI Obtained	-1.202 (0.153)	-1.182 (0.153)	-1.191 (0.154)
Log of Likelihood	-726.55	-725.71	-725.47

[a] Standard errors are shown in parentheses for all tables.

Table 5
Redlining and PMI

Loan Denial Models	Redlining by Race[a]	Redlining by Race with Tract Controls	Redlining by Income	Redlining by Income with Tract Controls
Race	0.341 (0.108)	0.310 (0.107)	0.355 (0.100)	0.313 (0.106)
Minority Tract	0.362 (0.142)	0.391 (0.147)		
Low Income Tract			0.440 (0.126)	0.325 (0.125)
PMI Obtained	-1.087 (0.187)	-1.077 (0.187)	-1.057 (0.189)	-1.041 (0.188)
PMI Obtained * Race	0.208 (0.332)	0.196 (0.330)	0.215 (0.295)	0.244 (0.330)
PMI Obtained * Minority Tract	-0.789 (0.356)	-0.796 (0.353)		
PMI Obtained * Low Income Tract			-1.057 (0.339)	-0.924 (0.387)
Log of Likelihood	-728.61	-723.15	-724.31	-720.14

[a] This specifications in the first and third columns exclude the tract level variables shown in Table 4. The specifications in columns two and four include these additional control variables.

Table 6

Race and Tract Income

Loan Denial Models	Low Income Threshold	Median Income Threshold[a]	High Income Threshold
Race	0.313 (0.106)	0.309 (0.107)	0.306 (0.108)
Minority Tract	0.170 (0.147)	0.387 (0.152)	0.379 (0.152)
Low Income Tract (Low Threshold)	0.325 (0.125)		
Low Income Tract (Medium Threshold)		-0.028 (0.105)	
Low Income Tract (High Threshold)			0.007 (0.090)
PMI Obtained	-1.041 (0.188)	-1.011 (0.190)	-0.886 (0.180)
PMI Obtained * Race	0.244 (0.330)	0.305 (0.354)	0.346 (0.371)
PMI Obtained * Minority Tract	-0.220 (0.393)	-0.462 (0.368)	-0.491 (0.391)
PMI Obtained * Low Income Tract (Low)	-0.923 (0.387)		
PMI Obtained * Low Income Tract (Medium)		-0.645 (0.309)	
PMI Obtained * Low Income Tract (High)			-0.638 (0.358)
Log of Likelihood	-719.67	-720.87	-720.79

[a] Low-income tracts have a median income <39,000 based on the medium threshold and a median income <46,000 based on the high threshold. These values are based on the Boston Metropolitan area median income and one standard deviation above the median income.

Table 7

Estimations Excluding PMI Applications

Loan Denial Models	Low Income Threshold	Median Income Threshold	High Income Threshold
Race	0.283 (0.110)	0.283 (0.110)	0.279 (0.112)
Minority Tract	0.141 (0.149)	0.359 (0.153)	0.330 (0.151)
Low Income Tract (Low)	0.285 (0.126)		
Low Income Tract (Medium)		-0.065 (0.108)	
Low Income Tract (High)			-0.017 (0.091)
Log of Likelihood	-647.86	-649.31	-649.45

Table 8
Estimations controlling for Lender Diversity

Loan Denial Models	Sample Excludes Lenders with No Applications in Low Income Tracts	Sample Excludes Lenders with No Loans in Low Income Tracts	Full Sample with Lender Dummy Variables
Race	0.391 (0.117)	0.371 (0.118)	0.299 (0.110)
Minority Tract	0.136 (0.152)	0.137 (0.152)	0.045 (0.160)
Low Income Tract (Low Threshold)	0.324 (0.129)	0.299 (0.130)	0.320 (0.133)
PMI Obtained	-1.001 (0.210)	-1.019 (0.211)	-1.245 (0.211)
PMI Obtained * Race	0.243 (0.350)	0.253 (0.351)	0.018 (0.378)
PMI Obtained * Minority Tract	-0.240 (0.387)	-0.228 (0.383)	0.030 (0.336)
PMI Obtained * Low Income Tract (Low)	-0.977 (0.387)	-0.939 (0.383)	-0.979 (0.334)
Log of Likelihood	-533.58	-522.38	-627.18
Number of Observations	1969	1929	2763

Table 9

Tract Risk and PMI

Loan Denial Models	Low Income Threshold	Median Income Threshold	High Income Threshold
Race	0.313 (0.106)	0.308 (0.107)	0.304 (0.108)
Minority Tract	0.174 (0.146)	0.390 (0.152)	0.380 (0.152)
Low Income Tract (Low)	0.321 (0.124)		
Low Income Tract (Medium)		-0.030 (0.105)	
Low Income Tract (High)			0.006 (0.090)
Rent to Value Ratio	0.396 (0.070)	0.456 (0.108)	0.452 (0.104)
PMI Obtained	-1.021 (0.190)	-0.992 (0.191)	-0.859 (0.180)
PMI Obtained * Race	0.259 (0.331)	0.320 (0.354)	0.372 (0.372)
PMI Obtained * Minority Tract	-0.242 (0.404)	-0.486 (0.367)	-0.500 (0.388)
PMI Obtained * Low Income Tract (Low)	-0.876 (0.408)		
PMI Obtained * Low Income Tract (Medium)		-0.601 (0.315)	
PMI Obtained * Low Income Tract (High)			-0.616 (0.358)
PMI Obtained * Rent to Value Ratio	-0.236 (0.340)	-0.263 (0.346)	-0.392 (0.341)
Log of Likelihood	-719.54	-720.72	-720.46

Table 10

Simultaneous Estimation of PMI and Loan Denial

Variables	(1) PMI Obtained	(2) Loan Denial
Race	0.11 (0.09)	0.32 (0.10)
Minority Tract	-0.60 (0.14)	0.14 (0.20)
Low Income Tract (Low Threshold)	0.35 (0.13)	0.34 (0.16)
PMI Obtained		-0.81 (0.52)
PMI Obtained * Race		0.25 (0.27)
PMI Obtained * Minority Tract		-0.24 (0.41)
PMI Obtained * Low Income Tract (Low)		-0.91 (0.41)
Log of Likelihood	-1739.0	

Endnotes

---

1. Outcome-based evidence of redlining arises from the study of credit flows at the neighborhood level.

2. The Equal Credit Opportunity Act (ECOA) of 1974 prohibits discrimination against mortgage applications for the racial or ethnic composition of the neighborhood in which the housing unit is located. See Ross and Yinger [15] for a detailed discussion of the ECOA.

3. See Schill and Wachter [17] for a short but careful discussion of CRA.

4. See the outcome-based studies by Shlay [20] for Baltimore; Bradbury, Case and Dunham [5] for Boston, Shlay [19] for Chicago, Avery and Buynak [3] for Cleveland, and Schafer and Ladd [16] for New York City, and Holmes and Horvitz [9]. Note that Holmes and Horvitz include a measure of neighborhood default risk using public foreclosure data. Such an approach was only feasible due to the extreme price swings and unusually high default rates in the Houston market during their sample period.

5. Recent work on the role of race and location in small business lending by Cavalluzzo and Cavalluzzo [8] and Blanchflower, Levine, and Zimmerman [4] also suggests that the race of the applicant, rather than the area of the loan, is more important.

6. Avery, Beeson, and Sniderman [2] find consistent evidence of income and racial redlining using data gathered from the Home Mortgage Disclosure Act, but their data do not contain the detailed borrower and loan characteristics available for the studies discussed in the text.

7 . The findings of Munnell et al. [13] that African-Americans experience adverse treatment in the mortgage market have been widely cited and debated. See Ross and Yinger [15] for a detailed survey and analysis of this debate.

8. Many variables used in the expanded Munnell et al. [13] specification are insignificant. These variables are left in the current analysis, as it is impossible to know a priori whether any of these variables will become significant once the PMI interactive terms are included in the estimation. All results in the paper are robust in the estimations from more parsimonious models that omit the supplementary tract and/or personal characteristics and include the additional 87 observations.

9. Three alternative approaches were considered for handling PMI denied applications: 1. treat PMI denied applications as simply an application without PMI, 2. allow the intercept for the model to vary by whether PMI was denied, and 3. fully interact PMI denied with neighborhood composition variables. All results in the paper also arise in these alternative specifications. The

decision to simply drop the observations was based on the strong empirical relationship between PMI denied and mortgage application denial, which argued against specification 1 in this note, and the fact that there were only 77 PMI denied applications of which only 7 were approved, which suggests that PMI denied coefficients in specifications 2 and 3 will be based on a very small number of idiosyncratic observations.

10. The specification contains three credit history variables. Consumer credit history is an ordinal variable constructed based on the following categories: no payment problems, one or two slow pay accounts, more than two slow pay accounts, insufficient history, delinquencies, and serious delinquencies. Mortgage credit history is an ordinal variable with categories: no payment problems, no mortgage history, one or two late payments, and more than two late payments. The public record default variable is one if a bankruptcy has been declared and zero otherwise. Note that the basic results are robust to alternative specifications that relax the assumptions imposed by using ordinal variables for mortgage and consumer credit history.

11. Lenders traditionally use the minimum of appraised value of the house or its purchase price as the value in the loan-to-value ratio, rather than the appraised value in all cases. Using the loan-to-appraised value ratio does not alter the results.

12. Aside from allowing the intercept to vary, the underwriting models for multi-family and rental units are restricted to be the same as single family, owner-occupied units after loan terms have been correctly adjusted to control for the flow of rental income. Specification tests conducted by Munnell et. al. provide no evidence to suggest that the underwriting model varies between these types of units. Nonetheless, we re-estimated all models in the paper with a subsample that drops multi-family and rental units. All results are robust to this change.

13. Munnell et. al. also examine whether the underwriting model varies between fixed and adjustable rate mortgages. Again, they find no evidence to suggest that the underwriting model differs beyond simply allowing the intercept to vary between the two models. We re-estimate all models in the paper using only fixed rate mortgages and find that all results are robust to this alternative specification.

14. In the analysis presented in this paper, the vacancy rate and the boarded-up rate are dummy variables equal to one when the variables are high (one standard deviation above the mean). Dummy variables are examined because the neighborhoods might be judged as either bad or good according to these criteria. Using other thresholds for vacancy and boarded-up rates had little effect on the results.

15. Very few mortgage applications were made for units in tracts with racial compositions between 30 and 70 percent, and therefore the variation of the minority tract threshold within these bounds has little effect on the results.

16. The specification also interacts applicant race with the PMI variables, but the coefficient estimates on these variables are always insignificant.

17. Moreover, officials at FannieMae confirm that exceptions were made during the early 1990s and that some loans were purchased that had LTVs above 0.8 and were not covered by PMI.

18. Lank and Nakamura [11, 12] suggest that assessment risk may play an important role in explaining redlining. Property assessments may be inaccurate in neighborhoods with low loan volumes leading to lower willingness of lenders to approve mortgages in these neighborhoods. We re-estimated all models including a variable that is one if application volume in a tract falls below 25 applications, as well as an interaction between this variable and PMI obtained. The coefficient estimate on the interaction between application volume and PMI is not statistically significant and the inclusion of these variables in the specification had no effect on the results. We chose focus on the specifications that control for rent-to-value ratio instead of low loan volume due to our concern that application volume may be endogenous to market level redlining.

19. Tootell [22] suggests that, rather than redline themselves, mortgage lenders may rely on private mortgage insurers to screen applications from minority neighborhoods, and Tootell [23] finds that private mortgage insurers are less likely to approve applications for units in minority neighborhoods. This conclusion must be interpreted with some care. In this study, only 77 loan applicants apply for PMI and have that application denied, and of those applications only 14 involve either a white applicant in a minority tract or an African-American applicant in a white tract.

20. Specifically, the model is identified by the assumption that only the actual realization of the PMI obtained variable influences loan denial and that the unobserved propensity to obtain PMI has no direct influence on denial. In this context, the causality through the discrete variable assumption is much more appealing that a traditional exclusion restriction. It makes sense that lenders should only care about whether the borrower actually obtained PMI, and it is almost impossible to imagine a variable that PMI companies would consider that can be reasonably excluded from the lender's underwriting model. See Brock and Durlauf [6] and Ross and Yinger [14, 15] for recent applications of this approach to identification.

21. It is notable that the coefficients on the racial composition of the tract are significant when the specification does not control for other tract variables including rent to value ratio.

22. The sum and standard errors are 0.327 (0.330), 0.305 (0.327), 0.617 (0.314), and 0.599 (0.358) for the models presented in columns 1 through 4, respectively. The standard errors for the sums are estimated using the correlation between the estimated parameters on the tract and the tract-PMI interaction variables. The estimated correlation was 0.38 for all four models.

23. The sum of the low-income and the low-income/PMI interaction coefficients for the low

threshold model (column 1) is 0.598 with a standard error of 0.370, which just misses statistical significance at the 90% level. Note that the estimated correlation is 0.29. These sums for the last two models (columns 2 and 3) are statistically significant, but the comparison is not very meaningful because redlining arises on racial composition rather than tract income when the medium and high thresholds are used.