Government-Sponsored Enterprise Secondary Market Decisions: Effects on Racial Disparities in Home Mortgage Loan Rejection Rates

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Abstract

This article describes the results of a study into possible racial discrimination on the part of government-sponsored enterprises (GSEs)—specifically Fannie Mae and Freddie Mac—that buy home mortgage loans on the secondary market. The article begins by laying out the problem: Racial minorities are much more likely than members of the majority population to be denied loans, and loan originators point to pressure from the secondary market as the cause. The role of the secondary market in the lending industry and other research into its effects on discrimination is reviewed. The article then outlines the residual difference approach used in this study to measure racial discrimination. This includes estimating loan rejection equations to compute the measure of discrimination both with and without taking into account the GSE effects. (The equations and their derivations appear in an appendix.) The results for five minority groups (Blacks, Asians, Hispanics, American Indians, and others) are described. The study results indicate that a broad generalization of lender discrimination cannot be explained by GSE discrimination.¹

Racial minority group members, particularly African Americans and Latinos, are less likely to be approved for home mortgage loans than are members of majority populations. In 1997 the *New York Times* reported that recently released data from the Home Mortgage Disclosure Act (HMDA) revealed that Blacks were twice as likely as Whites to be denied loans in 1996, about the same disparity as found in 1990 (*New York Times*, 1997). Denial rates for Federal Housing Administration (FHA) loans also reflect the same 2-to-1 ratio. Whether the loans are conventional home mortgage loans or loans backed by various Federal guarantees, minority rejection rates seem persistently to be higher than majority group rejection rates.

In 1992 the Boston Federal Reserve Bank issued its comprehensive analysis of racial disparities in home mortgage loan rejection rates, using HMDA data merged with applicant file data. The findings indicated what appeared to be discriminatory lending patterns. Although some people objected that the study was flawed because HMDA data fail to incorporate measures of creditworthiness, property values, and other related factors that lenders use in determining whether to accept or to reject a loan applicant (Munnell et al., 1992), the bank's analysis seemed to overcome these objections. The initial public response to the report was to denounce the revealed discrimination.

Finding apparent discrimination in mortgage lending has important consequences for public policy. Lenders who are subject to Community Reinvestment Act (CRA) requirements must demonstrate that they do not unreasonably exclude low- or moderate-income areas. A favorable CRA rating requires, among other things, the lender to demonstrate that it does not engage in a pattern of discrimination or other illegal credit practices. Without a favorable CRA rating, lenders may be publicly challenged when they seek to expand, restructure, merge, or make acquisitions. These public objections to an institution's minority lending patterns are based on HMDA data and often rest solely on the raw disparities revealed in virtually every metropolitan statistical area (MSA) in the Nation (Lind, 1996a, b).

Lenders objected to the conclusions drawn by the study. They contend, correctly, that the raw racial gaps in rejection rates observed in HMDA data alone do not prove discrimination. They point out that three types of data are omitted from the HMDA loan application record files: information on credit risk, property values, and saleability on the federally insured secondary market. The issues of credit risk and property values can be addressed using census data or additional (although time-consuming) methods adopted by the Boston Federal Reserve. The issue of loan saleability, however, has remained largely unaddressed. Lenders claim that they are not discriminating but rather are bound by stringent underwriting requirements imposed by government-sponsored enterprises (GSEs) in the secondary mortgage market that possibly have discriminatory results. Since increasing numbers of lenders are seeking to sell their loans on this secondary market, the omission of saleability information in HMDA data affects any assessment of the degree of mortgage discrimination in local metropolitan areas.

To test the lenders' contention, we investigated the effects of GSE decisions on racial gaps in mortgage lending. Mortgage lenders typically do not hold their loans; rather, they sell them to other institutions, including GSEs such as Fannie Mae and Freddie Mac. Our analysis stems from the premise that primary lenders may use the subsequent difficulty of selling loans to GSEs on the secondary market as a pretext for not approving loans to racial minority group members. The key question we ask is, "What would minority loan rejection rates have been if minorities had received equal treatment in the sales of loans to this secondary market?" In other words, we estimate the portion of the overall racial disparity in loan rejection rates that can be explained by GSE decisions.

To properly address how the saleability of loans affects the racial gap in lending, we devised an innovative method for combining HMDA information with the Census Tract File of the HUD-GSE public use data on Fannie Mae and Freddie Mac. Using this data set and our model we can determine:

- If there are racial disparities in first-time homebuyer loan acquisitions by GSEs.
- If measures of racial discrimination in mortgage lending disappear when GSE purchases are taken into account.

■ If any measured discriminatory lending patterns diminish through time once account is taken of GSE purchases.

The Role of Secondary Markets

Two complementary objections, both relating to the secondary market, have been raised against findings of lender discrimination based on HMDA data. One objection is that secondary markets help to spread lender risk and, therefore, ought to increase the flow of loans to low-income, moderate-income, and minority borrowers. In the presence of the secondary market, lender discrimination of the Arrow-Phelps type (statistical discrimination arising from the lender using race/ethnicity as a proxy for unobservable borrower credit risk characteristics to determine probability of default) ought to diminish. Furthermore, given the competition-enhancing effects of secondary market activities, lender discrimination of the Becker type (taste-based discrimination arising from a lender's preferences for doing business with different racial/ethnic groups) also ought to diminish. Failure to account for the effects of secondary market activities, therefore, may bias empirical results in favor of finding discrimination.

The second objection is that lenders must meet the GSEs' underwriting criteria. If we assume, for example, that Blacks are more likely to default than Whites and the underwriting criteria capture this, then a failure to take into account the lower chances that a Black loan will meet the secondary market buyers' underwriting criteria will bias empirical results in favor of finding discrimination by lenders. Of course, the underwriting criteria themselves may be racially discriminatory, a matter of separate and largely unexamined concern.

The literature describing secondary market effects on discrimination is scarce. Perhaps the best known review is found in John Goering and Ron Wienk's (1996) definitive volume, *Mortgage Lending, Racial Discrimination, and Federal Policy*. In that book, Robert Van Order, a former chief economist of Freddie Mac and director of housing finance analysis at the U.S. Department of Housing and Urban Development (HUD), details two aspects of secondary market effects. On the macro scale, Van Order (1996) sketches a simple model to show that even when lenders are reluctant to make loans to minorities and even if only nonminority loans are purchased on the secondary market, minorities will still benefit from secondary market transactions. Van Order assumes that lenders who hesitate to lend to minorities will in fact do so if minority interest rates are relatively high. Minorities also benefit from the secondary market because the supply of loans is greater and the prices paid for those loans will be lower, a result of increased competition.

Van Order's analysis can be used to show that if lenders are Arrow-Phelps discriminators, the presence of secondary market purchasers will reduce racial disparities in lending. The logic is that the statistical discriminators make fewer loans to minorities because they believe that Blacks are more likely to default than Whites. Although individual Blacks may have unknown or unobserved rates of default, they are members of a group with higher default rates and lenders use this information in their decisions. However, if the secondary market can assess individual risk better than the lender, such as by credit scoring or underwriting criteria based on large samples of loans over many circumstances, then lenders who sell to the secondary market can reduce their statistical risk of making minority loans. Of course, if the minority loan does not meet the underwriting criteria, it will be rejected. In this sense, then, omission of the secondary market decisions is likely to overstate the degree of statistical discrimination.

Van Order also considers a micro model of lender discrimination in the face of secondary market decisions. The focus is on risk sharing. GSEs and other actors in the secondary market assume credit risk and package mortgages so that they might be sold as "relative-ly homogenous securities or financed with homogenous debt in the capital markets" (Van Order, 1996). This creates a problem because GSEs must rely on the loan originators to send high-quality loans to Fannie Mae and Freddie Mac. The GSEs, therefore, establish guidelines and provide incentives for lenders and servicers to provide them with quality mortgages. Because neighborhood and borrower characteristics, as well as other factors, affect the quality of a loan, Van Order notes that GSE guidelines might rule out credit-worthy minority applicants as a way to avoid *adverse selection*.

Adverse selection occurs when lenders keep their most attractive loans and sell only the more risky ones. A lender on the brink of bankruptcy, for instance, might practice adverse selection. One can imagine that this strategy on the part of lenders would benefit high-risk and minority borrowers because lenders have no reason to engage in statistical discrimination as long as loans can be sold. If this were so, one might expect to find that GSEs hold a higher-than-average number of minority loans. Because the evidence shows, however, that minorities tend to be underrepresented in GSE portfolios, conjecture about adverse selection does not hold much merit. Thus, Van Order does present some findings that reject the hypothesis of discrimination by GSEs. Although the test is not a fully robust one, it nonetheless shifts some of the attention back to lenders themselves.

In a recent comprehensive review of studies of racial discrimination in mortgage markets, Helen Ladd (1998) points out that secondary markets pose a real puzzle to anyone analyzing patterns of discrimination. She writes:

Lenders in the secondary market buy loans from direct lenders and resell them. For present purposes, the important characteristic of this process is that the risks of default are shifted to investors in the secondary market, and it is not clear why loan originators such as banks need to pay attention to any race-specific probability of default. Provided the loan meets the standards imposed by the secondary market, originators of loans would have little or no incentive to avoid the additional risks they might perceive to be associated with some loans to minorities. (Ladd, 1998)

Here Ladd provides the most explicit statement of the hypothesis that we test: that discriminatory outcomes in loan rejection rates are the result of discrimination in the secondary market. She asks:

Are the guidelines in the secondary market discriminatory or applied in a discriminatory manner? If so, then discriminatory outcomes for borrowers could reflect unfair treatment not by the originators of loans, but rather by the lenders in the secondary market. (Ladd, 1998)

Cathy Cloud and George Galster (1993) also explore these questions and conclude that mortgage underwriting standards do affect majority and minority applicants differently. They note that neighborhood characteristics and property appraisals play important roles in underwriting and stand as possible barriers to minorities seeking credit:

Standard appraisal forms often are not designed to communicate clearly the nature and marketability of properties in diverse, inner-city neighborhoods; standards tend to denigrate properties in areas with growing numbers of renter-occupants and mixed land uses. (Cloud and Galster, 1993) In sum, there is ample theoretical basis for questioning whether the wide racial disparities in loan rejection rates might be attributable to secondary market discrimination, but little empirical evidence on the question.

Methodology

The study examined the role of two specific GSEs, Fannie Mae and Freddie Mac, in granting mortgages to homebuyers in the 23 largest MSAs in the United States. MSAs, as defined by the U.S. Office of Management and Budget, include cities of 50,000 or more or urbanized areas of 50,000 or more where there is a metropolitan population of at least 100,000.

Three data sets were used: the HUD-GSE data set for 1993–96, the 1990 U.S. census standard tape file, and the HMDA data set for 1992–96. These three data sets were combined to create two new data sets: a HUD-GSE/census data set and a census/HMDA data set. This permitted matching individual cases in the HUD-GSE or HMDA sets with the corresponding census tract data, allowing an analysis of individual experience while accounting for socioeconomic factors that may impact mortgage decisions (see exhibit 1).

Exhibit 1

Flow Chart for Equations



Conditions

Our sample was restricted to home purchase mortgage loans for owner-occupied dwellings with completed applications that were not withdrawn.

Model

The method we employ to measure racial discrimination in mortgage lending is called the *residual difference* approach. In a nutshell, this approach decomposes racial gaps in loan-rejection rates between the component that can be explained and that which cannot be explained by racial differences in characteristics. The unexplained gap is interpreted as being *discrimination*. Alternatively, the residual difference method permits the estimation of minority loan-rejection rates when minorities are treated the same as equally qualified Whites.

Because one of the qualifications that enters the lending decision is the probability that the loan will satisfy secondary market saleability requirements, we focus on producing a proxy for this probability measure by using data on loans actually acquired by GSEs. The method used to assess discrimination in HMDA data also can be used to measure what first-time homebuying percentages among Blacks would be if Blacks were endowed with the characteristics that make White borrowers attractive to lenders. This intermediate step permits us to evaluate how much of the anticipation of GSE acquisition of minority loans (as measured by our proxy) derives from racial differences in borrower characteristics and how much derives from possibly different treatment by GSEs of minority and nonminority first-time homeowner loans.

The four main dependent variables used in the study are bad credit, probability of being a first-time homebuyer, probability of a loan being sold to GSE, and loan rejection. Independent variables include characteristics of the borrower (gender, different race of applicant and co-applicant, same sex of applicant and co-applicant, household income, estimated bad credit); characteristics of the loan (size of loan, type of loan: FHA, U.S. Department of Veterans Affairs [VA], Farmers Home Administration [FmHA], or conventional); type of agency (Federal Deposit Insurance Corporation [FDIC], Federal Reserve Board [FRB], HUD, National Credit Union Association [NCUA], Office of the Comptroller of Currency [OCC], or Office of Thrift Supervision [OTS]); year; and ratio of amount requested to income. (For a detailed presentation of the equations used, see appendix.)

Results

Racial Distribution of Loans

Our analysis of 23 MSAs adds to the existing evidence that minority loans are underrepresented in GSE purchases (Bunce and Scheessele, 1996). We find that MSAs in western and southwestern States have the highest percentages of American Indian applicants, but still never more than three-quarters of 1 percent of the total. Anaheim, Los Angeles, New York, and Oakland have the largest percentages of Asian applicants, ranging from 12 to 19 percent of applicants. Atlanta, Baltimore, New York, and Washington, D.C. had the largest percentages of Black loan applicants; all at more than 10 percent. Eleven cities had more than 10 percent Hispanic loan applicants: Anaheim, Chicago, Dallas, Houston, Los Angeles, Miami, New York, Oakland, Phoenix, Riverside, and San Diego. The shares range from 10 percent in Dallas to 25 percent in Los Angeles to nearly 70 percent in Miami. However, these percentages of loan applicants do not always translate into high percentages of loans purchased by GSEs.

Blacks' share of all loan applications is twice that of their share of GSE loans. American Indian and Hispanic loans are also underrepresented in GSE purchases. What is interesting, however, is that the underrepresentation is not constant across MSAs. In Baltimore, Nashville, and Washington, D.C., Blacks' share of loan applications is 2.5 to almost 3 times their share of GSE loans. Although Hispanics' share of loan applications in Nashville is twice that of their GSE share, their share of loan applications in Washington, D.C. is about the same as their share of GSE loans. In Phoenix, there is a substantial underrepresentation of American Indians and Hispanics among GSE loans, but Blacks' share of all loans is only 1.8 times that of their share of GSE loans often exceeds their share of all loans, although there is a notable underrepresentation of GSE loans among Asians in Minneapolis-St. Paul and Cleveland, Ohio. To further underscore the variability of the measure of underrepresentation, we note that in Los Angeles, Black, Latino, and American Indian shares of GSE loans exceed their share of applications.

The broad pattern shows wide disparities in the number of Black, Hispanic, and American Indian loans held by GSEs compared to the minority representation among loan applicants. This disparity helps to motivate the discussion of how GSE decisions may affect lender decisions to reject minority loan applicants.

Exhibit 2



Minority Underrepresentation Among GSE Loans, 1996

Results of Residual Analysis

In the sections below, we describe the results obtained from three key aspects of the analysis: estimation of the effects of first-time homebuyers on secondary market loan sales, measurement of discrimination by GSEs, and the effects of GSEs on measured discrimination at the lender level. These results derive from analysis that generates measures of credit risk as a means of computing measures of discrimination. A summary of the preliminary steps in the analysis follows.

Rejection Rates With Bad Credit Proxy

One of the main criticisms of using HMDA data to measure discrimination is that the data set does not include a measure of borrower risk. Following the work of Myers and Chan (1995), we take advantage of the fact that reasons for loan denial are included, thus permitting us to create a proxy for "bad credit." We calculated the maximum likelihood estimates of coefficients in a logistic model of bad credit. Factors in the regressions include income, gender, owner-occupancy, and a vector of characteristics of the census tract and year. Effects of individual and census tract characteristics vary by MSA. In most MSAs, for example, females have higher probabilities of being rejected because of bad credit, but in Houston and Nashville, the coefficients are negative. High rental areas in New York predict lower credit risks, while high rental areas in Cleveland, Dallas, and Detroit predict higher credit risks. Overall, the models do not predict well; only about 50 to 60 percent of the cases are correctly classified. As a result, the bad credit variable predicted for rejected applicants is only slightly higher for accepted applicants across the MSAs. Notable, however, is the finding that the actual and predicted bad credit rates are larger for Blacks than for Whites, while the actual and predicted bad credit rates for Hispanics and American Indians are occasionally smaller than or equal to those for Whites. Asians generally have lower observed bad credit rates than Whites, according to these findings.

Effects of First-Time Homebuyers on the Sale of Loans

We calculated the maximum likelihood estimates of coefficients in logistic regressions for the probability that a loan sold to Fannie Mae or Freddie Mac was a first-time homebuyer loan. These equations were estimated separately by race. The model fit is quite good, with percentages correctly classified ranging from 65 to 100 percent.

We also looked at the determinants of the probability that a mortgage is sold to a GSE. Variables included type of loan, type of lender, loan-to-income ratio, census tract characteristics, and year. Consistently, we found that VA and FHA loans are considerably less likely to be sold to Fannie Mae or Freddie Mac than are conventional loans. FRB and HUD loans are considerably more likely to be sold to Fannie Mae or Freddie Mac than are OCC loans. National Credit Union loans, however, are often not more likely to be sold to these GSEs. FDIC loans have mixed effects across varying locations and races.

Exhibit 3 plots the minority/White ratio of the effects of first-time homebuyers on the probability that a loan is sold (given that it is actually made). In each entry the plot is the ratio of the minority-to-White odds ratios. When this ratio is less than 1, the White effect is larger than the minority effect. When this ratio is greater than 1, the minority effect exceeds the White effect. In the vast majority of MSAs, the White effect is greater than or equal to the overall minority effect.

■ In 20 of 23 MSAs, the odds ratio obtained from the American Indian regression is less than or equal to the White odds ratio.

- In 19 of 23 MSAs, the odds ratio obtained from the Black regression is less than or equal to the White odds ratio.
- In 18 of 23 MSAs, the odds ratio obtained from the Hispanic regression is less than or equal to the White odds ratio.
- In 15 of 23 MSAs, the odds ratio obtained from the other race equation is less than or equal to the White odds ratio.
- In 13 of 23 MSAs, the odds ratio obtained from the Asian regression is less than or equal to the White odds ratio.

In other words, in the majority of MSAs, the effects of being a first-time homebuyer on the likelihood that an originated loan is sold on the secondary market are smaller among minorities than the effects among Whites, particularly for American Indians, Blacks, and Hispanics. This can work in various ways:

- When the first-time homebuyer effect increases the chances that the loan is sold, the positive impact is larger for Whites than it is for minorities.
- When the first-time homebuyer effect reduces the chances that the loan is sold, the negative effect is smaller for Whites than it is for minorities.
- In some instances, the first-time homebuyer effect may be to increase the chances that the loan is sold for Whites, but to reduce it for minorities.

Exhibit 3 sorts the 23 cities based on the ratios found for American Indians, the group with odds ratios less than or equal to the White odds ratios in all but three metropolitan areas. The exhibit shows that with the exception of the few instances in which the American Indian/White ratio of effects is greater than 1, the relative effects for other races are almost always larger than the American Indian/White effect. That is, American Indian first-time homebuyers are more disadvantaged relative to Whites than first-time homebuyers among other races when it comes to the sale of their loans on the secondary market.

What we must appreciate, however, when looking at exhibit 3, is that this disadvantage is not of a large order of magnitude. Indeed, in many instances the odds ratios for both minorities and Whites are very close to 1, meaning that there is really no fundamental difference in the likelihood that a loan is sold on the secondary market, whether or not the borrower is a first-time homebuyer. The figure does show that this small effect is bigger for Whites than for minorities. However, it is unlikely that the wide gaps in loan availability between minorities and Whites stem principally from the racially differential impacts of being a first-time homebuyer on the chances that a loan is sold, once it is originated.

Discrimination by GSEs?

We computed estimates of residual discrimination in sale of loans to GSEs for each race and each year. These equations ask, "What would be the share of minority loans sold to Fannie Mae and Freddie Mac if minorities were treated the same as Whites?"

To interpret the results, we compare the actual GSE share with the *equal-treatment* share. In every MSA, the equal-treatment GSE share estimated for Blacks and Hispanics for each year is higher than the actual GSE share among Blacks. In every MSA except one, the equal-treatment GSE share among Asians is higher for each year than the actual





share. For American Indians, eight MSAs show 1 or more years in which the equaltreatment share is lower than the actual share.

The model, therefore, reveals differential treatment of equally qualified applications: Lenders are less likely to sell their minority loans to Fannie Mae or Freddie Mac. Nevertheless, two limitations in the model prevent us from concluding that this is clear evidence of discrimination by GSEs. First, because other GSEs (including Ginnie Mae) and other secondary market buyers, such as life-insurance companies and commercial banks, are not included in the sample used to run the regressions, the model tends to overpredict (for both Whites and minorities) the share of loans sold to Fannie Mae and Freddie Mac in any year. The favorable characteristics that predict that the loan would be sold to Fannie Mae or Freddie Mac might also predict that the loan would be sold to these other secondary market participants. In addition, while the underlying equation uses data from 4 years, an individual year's estimates are obtained by setting the year dummies equal to 1. This, in effect, amounts to a restriction of no interaction effects between year and other relevant variables. For whatever reason, then, the actual share is considerably lower than the predicted shares. This would be the case even if all loans were treated equally.

A second limitation is that the model does not measure discrimination by GSEs solely in terms of their refusal to purchase minority loans. Rather, the model captures an equilibrium decision between a lender's decision to hold a loan versus the secondary market's decision to purchase a loan. Obviously, lenders must attempt to sell the loan for GSEs to be able to decline or accept the purchase. Yet, we do not observe the entire sequence of decisions, only the result. Accordingly, when we use the term *GSE discrimination*, it should be interpreted in light of this form of equilibrium.

The Effects of GSEs on Residual Differences

To determine whether GSE behavior explains lender discrimination, we need to compute a measure of discrimination with and without taking GSE effects into account. This is done by estimating loan rejection equations for each MSA for each race across the 4 years. Combining years serves two purposes. First, it enlarges the sample for minorities in each MSA. Second, and more important, it smooths out any year-to-year disparities that arise from local market fluctuations.

The results from the preceding analysis yield proxies for two independent variables included in the loan rejection regressions—bad credit and the probability that a loan is not sold to a GSE. Other variables in these regressions include gender, same-sex applicants, ratio of loan to income, VA or FHA loan, census tract characteristics, lender type (FDIC, FRB, HUD, NCUA, OCC, OTS), and year.

For our final measure of discrimination by GSEs, we consider the effects of a loan's not being sold to a GSE on the probability that a loan is rejected by lenders. In every single equation, in every MSA, and for every racial group, when the probability that a loan is not sold to GSEs increases, so does the probability of that loan being rejected by lenders. In Minneapolis the estimated coefficients are virtually identical for Blacks, Asians, Hispanics, American Indians, and others. These values are smaller than the comparable value for Whites. In Boston the Black coefficient is larger than the White coefficient while the Asian and other-race coefficients are approximately the same as the White coefficients. In New York the coefficients are approximately the same for Whites, Blacks, Asians, Hispanics, and other races. In Miami, St. Louis, and Washington, D.C., the coefficient is about one-half the size of the White coefficient. In some cities, such as Boston, Phoenix, and San Diego, the American Indian coefficients are measurably larger than those for other groups.

What is most evident in the data is the remarkable similarity of absolute sizes of the notsold coefficients across races within jurisdictions. Even when there are differences, they are often very small. Although we cannot generalize from the nearly identical size of coefficients to identical marginal impacts across races, the coefficient size does affect the measurement of discrimination. If coefficients are identical, then we cannot attribute any residual discrimination to GSE behavior. At this point, we can only say that the coefficients are about the same for Whites and minorities across many MSAs.

On its face, then, the evidence does not seem to point to racial disparities in the impacts of sales to GSEs on the loan-rejection process. When looking only at loan sales to GSEs, the evidence does not show a higher rejection rate for minority than for nonminority loans when both share the same qualifications. Of course, there could be other factors involved. To partition the independent impacts of sales to GSEs on the racial disparities in rejection rates, we estimate the model with and without controlling for GSEs, and we then compute the equal treatment probabilities of loan-rejection rates. We do this with and without controlling for bad credit, recognizing the possibility that bad credit might be correlated with the not-sold variable, and recognizing the very low predictive value of the bad credit variable.

For example, consider New York. Between 1993 and 1996, White loan rejection rates were 12 percent. Loan rejection rates for Blacks stood at 18 percent; for Asians, 12 percent; for Hispanics, 16 percent; for American Indians, 16 percent; and for other races, 12 percent. When no account is taken of GSE decisions, the equal-treatment loan rejection rate for Blacks is 13 percent. This means that almost 80 percent of the actual gap

in White-to-Black rejection rates is unexplained. The percent of the gap attributed to the residual difference is:

Equal-treatment Black rejection rate - Black rejection rate

White rejection rate - Black rejection rate

or $(0.1333-0.1801) / (0.1210-0.1801) \times 100 = 79.18$ percent. When account is taken of the GSE decisions (that is, the probability that the loan is not sold to Fannie Mae or Freddie Mac) the equal treatment probability of rejection becomes 0.1546. The unexplained gap drops to approximately 43 percent, or $(0.1546-0.1801) / (0.1210-0.1801) \times 100 =$ 43.15 percent. Alternatively, we can consider equal treatment measured from the Whites' point of view. The actual White rejection rate is 0.1210. When Whites are treated the same as Blacks, the White rejection rate is 0.1869. When we also account for GSE decisions, the White rejection rate rises to 0.1983. From this perspective, then, the Black-White gap in rejection rates does not narrow—it widens. Thus, in New York at least, whether GSE decisions explain discrimination by lenders is sensitive to which base is used in measuring discrimination.

The New York findings contrast with those of Boston, where the residual differences are symmetric. Whether measured when Blacks are treated the same as Whites or when Whites are treated the same as Blacks, the residual difference is remarkably the same. This is because there is little difference in the equal-treatment rejection rates, however measured, between the model that takes GSE decisions into account and the one that does not. The equal-treatment Black rejection rate is 0.1056 when GSE decisions are not taken into account and is 0.0978 when GSE decisions are taken into account. This does result in a nontrivial change in the residual difference—from 72 percent to 81 percent—but it is a change in the wrong direction. That is, in Boston, GSE decisions do not explain the racial gap in loan rejection rates.

The results of estimation of residual difference with and without controlling for the probability that a loan is not sold to GSEs differ somewhat by race and are discussed below.

Effects Among Blacks

Across all 23 MSAs we find that observed rejection rates for Blacks exceed the equaltreatment rejection rates for Blacks, using a loan-rejection equation that controls for bad credit but not for GSE decisions. This finding reveals a measured discrimination against Blacks that is not due to observed characteristics of borrowers, lenders, loans, or neighborhoods. The Black-White gap in rejection rates unexplained by these characteristics ranges from 146 percent in Anaheim—meaning that in a discrimination-free environment, Black rejection rates would be less than White rejection rates—to 3 percent in Detroit (where the actual rejection rate and the discrimination-free rejection rates are almost the same), with most of the estimates in the 50- to 75-percent range. That is to say, without taking into account the chances that Fannie Mae or Freddie Mac will not buy the loan, our model estimates that for most MSAs only one-fourth to one-half of the racial disparity in loan-rejection rates can be explained by the included factors measuring lender, borrower, loan, and neighborhood characteristics.

When GSE effects are taken into account, we find in 20 of the 23 MSAs that the measured discrimination diminishes in nontrivial amounts. Everywhere but Boston, Detroit, and Houston, the equal-treatment rejection rates for Blacks are higher when one accounts for the probability that a loan might not sell to Fannie Mae or Freddie Mac. In Boston and Houston the differences are very small, amounting to less than 10 percent. The difference in the other direction is less than 10 percent in Dallas, Los Angeles, Miami, and Philadelphia as well. Across all of the MSAs there is a nearly 20-percent difference between the equal-treatment rejection rate that accounts for the GSE effects and the one that does not.

We conclude from this finding that without controlling for GSE effects, residual difference methods will tend to overstate the measured discrimination. This conclusion is tempered, however, by the fact that loans that do not sell to GSEs might still be good loans. However, to the extent that lenders gauge their lending decisions by the underwriting criteria of Fannie Mae and Freddie Mac, part of the Black-White gap in rejection rates can be attributed to the lower likelihood that Black loans will meet the GSE's requirements.

These results do not make clear, however, whether GSE decisions explain the huge residual gap in lending. Much of the discriminatory gap remains even after taking into account the probability that a loan might not be sold to Fannie Mae or Freddie Mac. In Anaheim the unexplained residual is 30 percent; in Atlanta, 28 percent; and in Chicago, 23 percent. In comparison, in Cleveland it is only 5 percent; and in Tampa, less than 1 percent. The discriminatory gap remains in most of the MSAs, with or without control for GSE effects.

In some cities the measured discrimination is sensitive to whether we compute the equaltreatment rejection rates on the Black base or the White base—that is, whether we compute the Black rejection rate when Blacks are treated the same as Whites or the White rejection rate when Whites are treated the same as Blacks. Still, it is remarkable that in more than one-half of the cases (14 of 23), the two measures are comparable to one another. For example, in Oakland, the White rejection rate is 13.46 percent; the Black rejection rate is 27.88 percent. Over the period from 1993 to 1996, the model controlling for GSE effects predicts that if Blacks were treated the same as Whites, the Black rejection rate would be 19.99 percent. If Whites were treated the same as Blacks, the White rejection rates is due to the unequal treatment of Blacks compared with Whites; 53 percent of the actual gap in rejection rates is due to the unequal treatment of Whites compared with Blacks.

In other cities the estimates are further off between the two comparisons of equal treatment. In St. Louis, for example, White rejection rates are 16.07 percent; Black rejection rates are 25.87 percent. When Blacks are treated the same as Whites, their rejection rates fall to 21.24 percent, explaining 47 percent of the racial gap. When Whites are treated the same as Blacks, their rejection rate rises to 23.08 percent, explaining 72 percent of the gap. In Tampa, the disconnect between the two measures is enormous. There, the White rejection rate is 16.84 percent; the Black rejection rate is 26.63 percent. When Blacks are treated the same as Whites, their rejection rates rise to 26.73 percent. When Whites are treated the same as Blacks, their rejection rates rise to 26.05 percent. The discriminatory differences are -1 percent versus 94 percent, a huge interpretive disparity between the two measures.

Notwithstanding these differences, however, the main conclusion is that in the majority of MSAs, controlling for GSE effects results in lowered measured discrimination. This is true whether we measure discrimination by treating Blacks the same as Whites or by treating Whites the same as Blacks. In all but two MSAs (Boston and New York), when measuring discrimination by treating Whites the same as Blacks, the residual difference is smaller when we account for GSE effects than when we do not.

Effects Among Hispanics

In nearly one-half of all MSAs the measured discrimination between Hispanics and Whites does not diminish when account is taken of the probability that loans will not be sold to GSEs. Overall, the difference between the two measures of discrimination is only about 5 percent. Out of the 11 cases in which the equal-treatment rejection rate for Hispanics decreases when GSE effects are taken into account, only 3 differ by more than 10 percent. Of the 12 cases in which the discriminatory residual is smaller when GSE effects are accounted for, only 4 show a difference of more than 12 percent. In other words, among Hispanics, the GSE effects are much smaller than they are among Blacks.

Exhibit 4 shows the relationship between the GSE effects among Blacks and the effects among Whites. The graph shows the ranked order of ratios of equal-treatment rejection rates with and without controls for GSE effects. When the probability of nonsales to GSEs is not taken into account and the ratio is greater than 1, the equal-treatment minority rejection rate is underestimated. Or, equivalently, when the ratio is greater than 1, failure to take GSE effects into account will result in an overestimate of the discriminatory residual. We graph the Hispanic series, ranked from the lowest ratios to the highest ratios, and also show the comparable Black series in the same cities.

Exhibit 4

Ratio of Equal Treatment Rejection Rates With and Without Control for GSE Effects



The exhibit clearly shows that the Black overestimate of the discriminatory residual (and thus the understatement of the equal-treatment rejection rate) arising from the failure to account for GSE decisions largely exceeds the Hispanic overstatement in almost all MSAs. Moreover, the exhibit reveals a great fluctuation in the Black ratio when mapped against the sorted Hispanic ratio. This means that although the rankings of the Black and Hispanic ratios are similar, there are often substantial differences between the two within a given MSA. What is the nature of this difference? In almost every MSA the Black ratio is larger than the Hispanic ratio. That is to say, failure to include GSE effects overstates by a larger amount the discriminatory residual among Blacks than it does among Hispanics in many MSAs.

Effects Among Asians

One of the main findings of this research is that although Asians generally have low rejection rates, often lower than Whites, they do face discrimination. Their equaltreatment rejection rates would be lower than their actual rejection rates in 14 of the 23 MSAs, and the equal-treatment rejection rates that take GSE effects into account are lower in 11 of the 23 MSAs than those recorded when GSE effects are not taken into account. These differences arise against a backdrop of extremely small gaps in actual rejection experiences between Asians and Whites. Exhibit 5 plots the ratio of Asian to White rejection rates in 23 MSAs. When this ratio is greater than 1, Asians are disadvantaged. When this ratio is less than 1, Asians are advantaged. Exhibit 5 shows that the Asian-White rejection gap favors Asians in 10 out of 23 cases, and that in another 6 instances, the Asian rejection rate is greater than the White rejection rate by less than 10 percent. Of course, there are some major gaps in the remaining cities. In Washington, D.C., for example, the Asian rejection rate is 8.43 percent; the White rejection rate is 6.18 percent. In Chicago, the Asian rejection rate is 8.92 percent; the White rejection rate is 6.81 percent. In both cities, then, Asian rejection rates are 30 percent higher than White rejection rates. And, of course, this large gap is due to the fact that the rejection rates for both Whites and Asians in those two cities are so low.

Effects Among American Indians and Others

In all but three MSAs, the equal-treatment rejection rate for American Indians is larger when control is made for GSE decisions than when it is not. Although the actual American Indian rejection rate is consistently higher than the equal-treatment rejection rate, the effect of controlling for the probability that a loan will not be sold to Fannie Mae and Freddie Mac is to reduce the size of the unexplained residual gap in rejection rates. In Anaheim, Los Angeles, and Nashville, this reversal is not seen. But in 20 other MSAs, we find that failure to account for GSE decisions results in an upward bias in the estimate of discrimination.

The remaining racial category, *other*, also shows this pattern. In all but two MSAs, New York and Philadelphia, failure to account for GSE decisions will bias the measure of discrimination upward. Of course, this finding is sensitive to how we measure discrimination. In both conclusions above, we have measured discrimination using the White group as the reference group by computing the rejection rates that American Indians, or others, would obtain if they had been treated the same as Whites.

Taken together, the results demonstrate that GSE decisions do tend to account for some of the measured discrimination facing Blacks, American Indians, and others. Among Hispanics and Asians, the results differ from location to location. Thus, an overriding consideration in examining GSE effects on discrimination is the variation across races and location.



Ratio of Asian Rejection Rate to White Rejection Rate, 1993–96

Does GSE Discrimination Explain Disparities in Loan Rejection?

The conclusion that measures of Black, American Indian, and other race discrimination are upward biased by failure to account for GSE decisions must be tempered by the fact that we do not know whether these latter decisions are themselves discriminatory. Is it possible that discrimination by GSEs explains racial gaps in lending?

To answer this question, we perform an experiment that conceptually eliminates unequal treatment in sale of loans to GSEs. Given a residual difference in the probability that a loan is sold to Fannie Mae or Freddie Mac, we wish to know what the measured discrimination in loan-rejection rates would be if that residual difference were eliminated. For example, what would be the loan rejection rates of Blacks if they were treated as Whites in every step of the loan process, including the sale of loans to GSEs? In this hypothetical situation, we show that the loan-rejection rates would be about 3 percentage points lower in Minneapolis-St. Paul (13 percent versus 16.6 percent); 3 percentage points higher in Boston (12.97 percent versus 9.78 percent); and less than 1 percentage point lower in New York (14.71 percent versus 15.46 percent).

Exhibit 6 sums up the results. If the overall equal-treatment rejection rate is higher than the equal-treatment rejection rate that accounts for discrimination by GSEs, we then contend that discrimination by GSEs explains part of the lending gap. If the equal treatment value without accounting for racial differences in GSE effects is equal to or lower than the corresponding value that accounts for racial differences in GSE effects, we then conclude that GSE discrimination does not explain racial lending gaps.

MSA	Blacks	Asians	Hispanics	American Indians	Other
Anaheim	yes	no	yes	no	no
Atlanta	yes	no	yes	no	yes
Baltimore	yes	yes	no	no	yes
Boston	no	no	no	yes	no
Chicago	yes	yes	no	no	no
Cleveland	yes	yes	no	yes	yes
Dallas	no	yes	no	no	yes
Detroit	yes	no	no	yes	yes
Houston	no	yes	no	no	yes
Los Angeles	no	no	no	no	yes
Minneapolis-St. Pau	l yes	yes	yes	yes	yes
Miami	yes	yes	no	yes	yes
Nashville	yes	yes	yes	no	yes
New York	yes	no	no	yes	no
Oakland	yes	no	no	yes	yes
Philadelphia	no	yes	yes	yes	no
Phoenix	yes	yes	yes	yes	yes
Riverside	yes	yes	no	no	no
St. Louis	yes	yes	yes	yes	yes
San Diego	yes	no	no	no	no
Seattle	yes	yes	yes	no	yes
Tampa	yes	no	no	no	yes
Washington, D.C.	yes	yes	no	no	yes

Does GSE Discrimination Explain Racial Gaps in Loan Rejection Rates?

Exhibit 6

There are no consistent patterns across racial groups or across MSAs. In many MSAs, discrimination by GSEs can account for some of the high rejection rates of Blacks and others. Among other racial groups, however, there are as many MSAs in which there is no such finding as there are ones in which the effect seems to hold. Even here, the amount explained is small. Thus, we cannot conclude that there is a consistent pattern of racial discrimination by GSEs that can explain the racial disparities in loan rejection rates.

Conclusion

Taken at face value, the lenders' contention that Blacks and other racial minority group members are more likely than Whites to be denied loans because their loans are less likely to be sold on the secondary market to Fannie Mae and Freddie Mac seems merited. Our findings do reveal that the probability that a loan would not sell on the secondary market systematically increases the probability that it will be rejected by the lender. Our findings also support the view that Black and Hispanic loans are often less likely to sell on the secondary market than White loans. There are a few exceptions to this pattern, but the contention that loans to minorities have lower rates of sale to Fannie Mae and Freddie Mac appears valid at first glance. Further review of the findings, however, reveals a major weakness of this argument. First of all, the marginal impact of the probability of not being sold to a GSE, although statistically significant, is small. In fact, it is so small that even large differences in actual probabilities that loans are not sold to GSEs cannot explain the substantial racial differences in loan-rejection rates. Second, and more important, when one evaluates the impact of sale to GSEs by comparing discriminatory residuals with and without control for GSE decisions, the results are not consistent and at times, are contradictory. For example, controlling for GSE decisions causes an increase in the equal-treatment rejection rates for Blacks, Asians, Hispanics, American Indians, and other races in Minneapolis-St. Paul over the value computed without controlling for these decisions. Thus, in Minneapolis-St. Paul, failure to control for GSE behavior appears to create an overestimate of the degree of discrimination by GSEs against minorities. Yet, in Boston, the equal-treatment rejection rates of Blacks, Asians, and Hispanics that control for GSE decisions are lower (although often by a small amount) than those that do not. Thus, in Boston, the contention that GSE decisions help to explain the apparent discriminatory gap finds little support. In New York, when controlled for GSE decisions, the equal-treatment rejection rates for Blacks are higher; for Asians, lower; for Hispanics, lower; for American Indians, higher; and for other races, lower, than without the control. In a nutshell, then, the results do not provide consistent and compelling evidence that GSE behavior lies at the root of unequal loan-rejection rates at the lender level.

To look at this in another way, we have computed the ratio of the equal-treatment rejection rates with and without controlling for GSE disparities. The numerator is the equaltreatment rejection rate using the estimated probability that a loan is not sold to Fannie Mae or Freddie Mac. The denominator is the equal-treatment rejection rate using the equal-treatment (discrimination-free) measure of the probability that a loan is not sold to Fannie Mae or Freddie Mac. A ratio greater than 1 indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to 1 indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.

Exhibits 7 to 11 reveal that it is not possible to draw a conclusion that holds across all MSAs for all minority groups. Exhibit 7 does show that in most instances the ratio is greater than 1 for Blacks, but there are several MSAs for which the ratio is very close to 1 or slightly less than 1. Among Asians, the ratio is nearly equal to 1 across all MSAs, but only because it is above 1 in approximately one-half and below 1 in the other half. Among American Indians, the ratio is equal to or below 1 in a large share of the MSAs, but the few MSAs where the ratio is substantially above 1 causes the mean for all MSAs to rise to 1.098. Among Hispanics, the mean for all MSAs is visibly below 1, at 0.96, with a handful of MSAs registering values above 1. For other races, the ratio is visibly close to 1 in all but a few cases where the ratio is substantially above 1, causing the mean to rise to approximately 1.118.

We conclude from this summary of the residual discrimination analysis that we cannot generalize that GSE discrimination causes lender discrimination. That is not to say that in some locations or for some groups, racial disparities in GSE purchases might not contribute to racial disparities in loans by lenders. We can state, however, that the broad pattern of lender discrimination, particularly against Blacks, Hispanics, and American Indians, cannot be explained by GSE discrimination.

The observed racial disparity in lending, therefore, must arise from the lenders' own behavior, and not, as they argue, from the difficulty of selling those loans to GSEs. When we conceptually rid the market of racial disparities in GSE decisions, we find that the equal-treatment rejection rates are lower only by a slight amount overall for Blacks and indeed, are higher among Hispanics. This finding is hardly what is needed to absolve lenders of culpability in racial-lending disparities.

Exhibit 7



Ratio of Equal-Treatment Rejection Rates, Blacks (mean = 1.11)

Note: The numerator is the equal-treatment rejection rate using the estimated probability that a loan is not sold to Fannie Mae or Freddie Mac. The denominator is the equal-treatment rejection rate using the equal-treatment (discrimination-free) measure of the probability that a loan is not sold to Fannie Mae or Freddie Mac. A ratio greater than 1 indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to 1 indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.

One finding about discrimination emerges consistently. No matter how one computes the discriminatory residual and whether or not GSE decisions are taken into account, a nontrivial unexplained residual difference in loan-rejection rates between Blacks and Whites remains. In Boston, the lowest computed Black discriminatory residual is 72 percent; in Minneapolis, it is 32 percent; and in New York City, 43 percent. These results are on the same order of magnitude in Boston and Minneapolis when the computation is performed in an alternative way, that is, when Whites are treated the same as Blacks rather than Blacks the same as Whites. In New York, we estimate that when Whites are treated the same as Blacks, their rejection rates soar above the actual rejection rates of Blacks. Thus, even though the resulting discriminatory residual in New York differs in order of magnitude depending on which comparison is made, the direction of the discrimination remains the same: an adverse impact on Blacks.

1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0 Atlanta Dallas New York Boston Tampa -os Angeles Detroit Riverside Seattle Houston Phoenix Miami St. Louis Minneapolis-St.Paul Nashville Anaheim San Diego Oakland Chicago Philadelphia Cleveland Washington, D.C. Baltimore

Exhibit 8



Note: The numerator is the equal-treatment rejection rate using the estimated probability that a loan is not sold to Fannie Mae or Freddie Mac. The denominator is the equal-treatment rejection rate using the equal-treatment (discrimination-free) measure of the probability that a loan is not sold to Fannie Mae or Freddie Mac. A ratio greater than 1 indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to 1 indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.

It is difficult to draw identical conclusions with respect to other racial groups. For example, Asians in Minneapolis would have higher rejection rates than their actual rejection rates in an equal-treatment world. But then, Asian rejection rates are lower than White rejection rates in that MSA. In Boston and New York, Asian rejection rates would be lower in an equal-treatment world, even lower than the actual White rejection rates. Depending on whether one controls for GSE decisions or not, Hispanic equal-treatment rejection rates are higher or lower than their actual rejection rates in Minneapolis, but they are lower in Boston and New York. In other words, the findings for other races is particularly idiosyncratic with respect to location.



Ratio of Equal-Treatment Rejection Rates, Hispanics (mean = 0.96)

Note: The numerator is the equal-treatment rejection rate using the estimated probability that a loan is not sold to Fannie Mae or Freddie Mac. The denominator is the equal-treatment rejection rate using the equal-treatment (discrimination-free) measure of the probability that a loan is not sold to Fannie Mae or Freddie Mac. A ratio greater than 1 indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to 1 indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.

Our conclusion from the study, as it applies to public policy, therefore, is that extraordinary model sophistication and estimation upholds the finding of wide unexplained disparities in loan-rejection rates between Black and White applicants for home mortgage loans in HMDA data. Although these unexplained disparities can be explained theoretically by differences in the probability of not being sold on the secondary market or even by racial disparities in secondary markets, our findings for these 23 MSAs do not support that supposition.

Ratio of Equal-Treatment Rejection Rates, American Indians (mean = 1.098)



Note: The numerator is the equal-treatment rejection rate using the estimated probability that a loan is not sold to Fannie Mae or Freddie Mac. The denominator is the equal-treatment rejection rate using the equal-treatment (discrimination-free) measure of the probability that a loan is not sold to Fannie Mae or Freddie Mac. A ratio greater than 1 indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to 1 indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.



Ratio of Equal-Treatment Rejection Rates, Other (mean = 1.118)

Note: The numerator is the equal-treatment rejection rate using the estimated probability that a loan is not sold to Fannie Mae or Freddie Mac. The denominator is the equal-treatment rejection rate using the equal-treatment (discrimination-free) measure of the probability that a loan is not sold to Fannie Mae or Freddie Mac. A ratio greater than 1 indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to 1 indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.

Appendix

Equations Used in Residual Analysis

Let R^k be the loan-rejection rate of the k^{th} group. For an individual loan applicant this value is equal to 1 if the borrower is denied a loan; otherwise, it is equal to 0. Across all members of the k^{th} group this value can be summed and divided by the number of loan applicants in the k^{th} group to yield the percentage of *k*-group applicants who are denied loans.

The loan rejection rate depends on the following variables:

- W = a vector of characteristics of the loan, including Federal Housing Administration or U.S. Department of Veterans Affairs versus conventional loans and the amount requested.
- X = a vector of characteristics of the applicant(s), including a proxy for bad credit, gender of applicant and coapplicant, race of applicant and coapplicant, and income of applicant and coapplicant.
- Y = a vector of lender characteristics, including whether it is Federal Reserve Board, National Credit Union Administration, Office of the Comptroller of the Currency, Office of Thrift Supervision, and so on, and whether it is a large or small lender.
- a vector of census tract characteristics, including median housing prices, family income, poverty rates, mobility rates, percentage minorities, age distribution, and percentage of owner-occupied units.
- P(NS) = the probability that the loan will not be sold on the secondary market.
- P(ft) = the probability that a loan purchased by a GSE is a first-time homebuyer loan.

Model

Consider the following logistic regression equation for the probability that a Black loan applicant is rejected:

$$R^{b} = \frac{1}{1 + \exp(-(\upsilon^{b}W^{b} + \phi^{b}X^{b} + \chi^{b}Y^{b} + \psi^{b}Z^{b} + \omega^{b}P(NS)^{b})}.$$
(1)

where υ , ϕ , χ , ψ , and ω are coefficients to be estimated. Similarly, we have the following for White applicants:

$$R^{w} = \frac{1}{1 + \exp(-(\upsilon^{w}W^{w} + \phi^{w}X^{w} + \chi^{w}Y^{w} + \psi^{w}Z^{w} + \omega^{w}P(NS)^{w})}.$$
(2)

The percentage of the rejection gap that cannot be explained by W, X, Y, Z, and P(NS) is a measure of discrimination. Or,

$$D = \frac{\widetilde{R}^b - R^b}{R^w - R^b}.$$
(3)

where R^b is the equal-treatment value of loan-denial rates for Blacks. This rate is equal to the value of the rejection rates for Blacks when Blacks have the same coefficients (or treatment) as equally qualified Whites, or

$$\widetilde{R}^{b} = \frac{1}{1 + \exp(-(\upsilon^{w}W^{b} + \phi^{w}X^{b} + \chi^{w}Y^{b} + \psi^{w}Z^{b} + \omega^{w}P(NS)^{b})}$$
(4)

The problem, however, with this analysis is that we do not directly observe P(NS), the probability that the loan is not sold to Fannie Mae or Freddie Mac or elsewhere on the secondary market. Focusing specifically on GSE purchases, we know only whether an approved loan is sold. A proxy for P(NS) can be obtained from data on GSE purchases by using a derivation from Bayes' rule (Freund, 1972).

Note that what is observed is the conditional probability that a loan is sold to a GSE, given that it was approved. We do not know the unconditional probability that a loan will be sold to a GSE from either the HMDA data, which does not include details of which loans were sent for review and which were declined by the secondary purchaser, or from the HUD-GSE data, which only includes approved loans. However, we know from Bayes' rule that

$$P(S \mid O) = \frac{P(S) \cdot P(O \mid S)}{P(O)}$$
(5)

where S means that the loan was sold and O means that the loan was originated. Note that all loans sold by the lender must have been originated so we can obtain a measure of the unconditional probability that a loan will not be sold from

$$P(NS) = 1 - P(S) = 1 - P(S \mid O) \cdot P(O).$$
(6)

A proxy for the lender's probability that the loan will not be sold can be estimated by the product of two separately obtained probabilities:

I The conditional probability of selling a loan on the secondary market.

The probability that the loan was originated.

The second of these two probabilities is, unfortunately, tautologically related to the dependent variable, *R*. However, previous year's data from a given lender can be used to estimate for each racial group the likelihood of rejection controlling for location. Specifically, for the *j*th lender and the *i*th census tract for racial group *k*, the estimated probability of origination in time *t* is the origination rate for the *j*th lender in the *i*th census tract for racial group *k* in period t-1. In other words,

$$\hat{P}_{it}^{jk}(O) = P_{it-1}^{jk}(O) \tag{7}$$

This can be computed simply for all lenders that made loans in given census tracts. To simplify matters further and to account for the continuing controversy over whether smaller lenders who make very few minority loans should be subject to CRA rules, we restrict the analysis to those lenders that made at least 250 loans in years t and t-1 and at least one minority applicant in census tract I in year t if there is at least one minority applicant in census tract I in year t if there is at least one minority applicant in census tract I in year t-1. Previous analysis suggests that by restricting the sample to lenders with 250 or more loans, we eliminate or reduce the number of cases where the above estimate cannot be obtained.²

The first of the two probabilities, the conditional probability that a loan is sold on the secondary market, most likely is a function of the decision apparatus of the buyers of these loans. Fortunately, the HUD-GSE data are well-suited for incorporating GSE decisionmaking into the computation of lender outcomes. This is accomplished through a two-step method.

First we estimate the probability that the GSE purchases a first-time homebuyer loan. Denote this probability by P(ft). Then we can estimate for each group k:

$$P(ft)^{k} = f(W', X', Y', Z'),$$
(8)

where primes denote the fact that these independent variables are a proper subset of those listed in the rejection equation. This equation can be estimated using the HUD-GSE census tract data to obtain coefficients that, once applied, permit the calculation of predicted values of P(ft) for each loan that is sold. This predicted value, along with other variables relevant to the lenders' and secondary-market buyers' decisions, are then included to predict the probability that the loan is sold:

$$P^{k}(S \mid O) = f(W'', X'', Y'', Z''; \hat{P}(ft)),$$
(9)

where the double prime denotes that these independent variables are proper subsets of those listed in the rejection equation, but different from those in the first-time homeowner sale equation.

Armed with a measure of the conditional probability that a loan is sold on the secondary market and an estimate of the probability that a loan is sold, we can then derive a proxy for the probability that a loan will not be sold on the secondary market and thus is rejected by the lender. This probability of rejection is estimated separately for minorities and nonminorities, and the residual difference analysis proceeds as detailed previously.

The novel aspect of this investigation is the preliminary estimation of the probability that a GSE-purchased loan is a first-time homebuyer loan. The logic of including the predicted value of this variable in the loan-sale equation is that loans that can meet the stringent requirements of GSEs often are less costly and move more quickly.³ Some analysts claim that the GSEs, particularly Freddie Mac, fail to pursue minority first-time homebuyer loans in the same proportions as the industry at large (Lind, 1996a, b).

To test the hypothesis that the problem is not discrimination by lenders but discriminatory behavior by GSEs as secondary market underwriters, we can predict from equations (8) and (9) equal-treatment probabilities of nonsale of loans in equation (6), holding constant the predicted probability of originating the loan. In other words, we can isolate the impact that possible discrimination by GSEs plays in contributing to racial gaps in rejection rates. Obviously, if the marginal impacts of P(NS) on the rejection rates are large, then changes in the probabilities of sale arising from possible discrimination by GSEs could have nontrivial impacts on rejection rates.

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Notes

- 1. To view the complete data used in this study, see "The Effects of GSE Secondary Market Decisions on Racial Disparities in Loan Rejection Rates" online at www.hhh.umn.edu/centers/wilkins/hud.pdf.
- 2. Of course, this estimation forces a year-to-year equality in origination rates in particular census tracts for particular racial groups. An alternative is to estimate a growth parameter r from data on all census tracts for all years from 1992–96 to obtain

$$\hat{P}_{it}^{jk}(O) = \hat{\rho}^{k} \cdot P_{it-1}^{jk}(O).$$

Knowing the values for ρ for each racial group would be important and valuable in its own right for policymaking, but it also provides a useful adjustment to the strong assumption that there is no growth in origination rates for specific racial groups.

3. Freddie Mac (1996) asserts that its new automated underwriting assures that loan costs are lower and that processing is faster. Still, both Freddie Mac and Fannie Mae are known to exert substantial influence on overall market underwriting standards.

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