

***Final Report***

**The Effects of Government-Sponsored Enterprise (GSE)  
Secondary Market Decisions on Racial Disparities in  
Loan Rejection Rates**

**Submitted to:**

**U.S. Department of Housing and Urban Development  
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## 1. Introduction

This report summarizes the results of a statistical system designed to investigate the effects of government sponsored enterprise (GSE) decisions on racial gaps in mortgage lending. Mortgage lenders typically do not hold their loans, but 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 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.

Initially, we provide some background on racial gaps in mortgage lending. Then we detail our methodology (a multi-equation estimation system), summarize the equation structure of the model, and describe the data used to estimate the model. We then present the entire results for the 23 metropolitan statistical areas (MSAs) included in the sample. In a final section we discuss policy implications.

## 2. Background

### 2-1. The Problem

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.<sup>1</sup> Whether the loans are conventional home mortgage loans or loans backed by various federal guarantees, minority rejection rates are consistently higher than majority rejection rates.

In 1992, the Boston Federal Reserve Bank issued its comprehensive analysis of racial disparities in home mortgage loan rejection rates, using Home Mortgage Disclosure Act (HMDA) data merged with applicant file data. The findings indicated what appeared to be discriminatory lending patterns. While some people objected that the study was flawed because HMDA data fail to incorporate measures of creditworthiness, property values and 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.

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<sup>1</sup> “Rejections for Mortgages Stay Higher for Blacks,” *New York Times*, CXLVI(50,875), August 5, 1997, 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 found in 1990. Denial rates for FHA loans also reflect the same 2 to 1 ratio.

The finding of 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, that the lender demonstrate 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, February 1996, April 1996).

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 (LARS) files: information on credit risk, information on property values, and information about 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 saleability of loans, however, has remained largely unaddressed. Lenders claim that they are not discriminating, but rather, that they are bound by stringent underwriting requirements (possibly discriminatory) imposed by government-sponsored enterprises (GSEs) in the secondary mortgage market. Since increasing numbers of lenders seek 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.

In order to address properly how the saleability of loans affects the racial gap in lending, and thus to test the lenders' contention, 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:

- a) whether there are racial disparities in first-time home buyer loan acquisitions by GSEs;
- b) whether measures of racial discrimination in mortgage lending disappear once account is taken of expectations about GSE purchases;
- c) whether any measured discriminatory lending patterns diminish through time once account is taken of GSE purchases.

## **2-2. The Role of Secondary Markets**

Two complementary objections, both relating to the secondary market, have been raised against findings of lender discrimination based 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 (i.e., 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 (i.e., taste-based discrimination arising from a lender's preferences for doing business with different racial/ethnic groups) ought to diminish also. 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 that blacks are more likely to default than whites and the underwriting criteria capture this higher likelihood, then a failure to incorporate in discrimination studies 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 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, details two aspects of secondary market effects. On the macro scale, Van Order sketches a simple model to show that even when lenders are reluctant to make loans to minorities and even in a world where only nonminority loans are purchased on the secondary market, minorities will benefit from secondary market transactions. Van Order assumes that lenders who are hesitant 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, the loan 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. Here 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 “relatively homogenous securities or financed with homogenous debt in the capital markets” (Van Order, p. 342). This creates a problem in that 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. Since neighborhood and borrower characteristics, and 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, again, 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. Since the evidence shows, however, that minorities tend to be underrepresented in GSE portfolios, this conjecture about adverse selection doesn’t hold much merit.

Van Order does present some findings rejecting the hypothesis of discrimination by GSEs. While 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 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, p. 47)

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, p. 47)

Cathy Cloud and George Galster also explore these questions and conclude that in fact 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. They say:

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, p. 116 )

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.

### **3. Methodology**

This section explains in detail how the data was analyzed. (For the replication of the study, refer to the *programmer's guide*, which is provided separately.) In presenting our methodology we discuss five areas: 3-1) study area, 3-2) data sets, 3-3) assumptions and conditions, 3-4) equations, and 3-5) definitions of the selected variables.

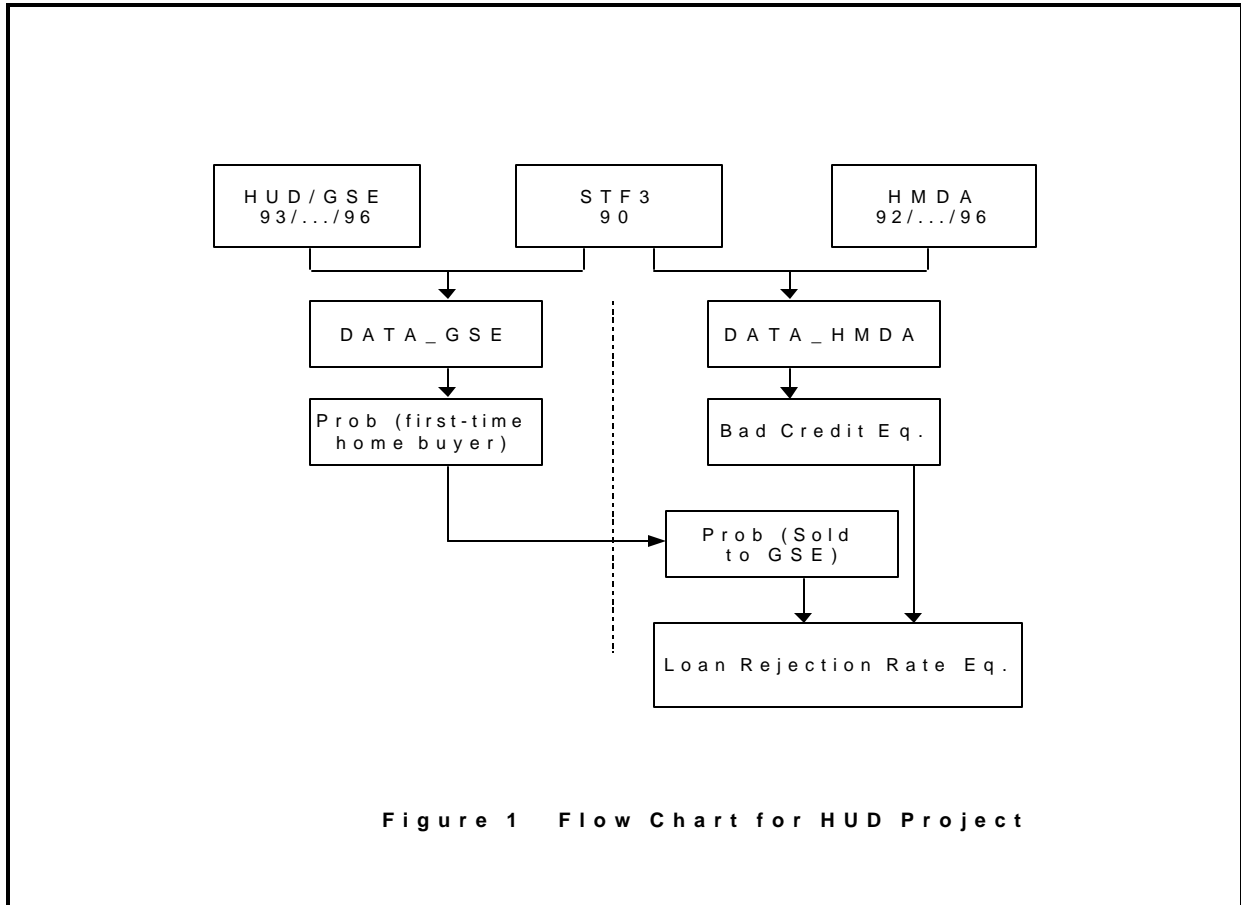
#### **3-1. Study Area**

The study examined the role of two specific government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, in granting of mortgages to home buyers in the 23 largest metropolitan statistical areas (MSAs) in the United States. MSAs are defined by the U.S. Office of Management and Budget to 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. Such areas may be designated as Consolidated Metropolitan Statistical Areas (CMSAs) when they have a population of one million or more, include separate component areas that meet statistical criteria, and have local support for the component areas. The component areas within CMSAs are designated Primary MSAs (PMSAs). This study evaluated both PMSAs and MSAs and selected the 23 largest of the combined categories. The complete list of MSAs studied and their designation as an MSA or PMSA is found in Table 1-1.

#### **3-2. Data sets**

This study used three data sets: the Department of Housing and Urban Development Government-Sponsored Enterprise data set (HUD/GSE) for 1993 through 1996, the 1990

U.S. Census Standard Tape File (STF3), and the Home Mortgage Disclosure Act data set (HMDA) for 1992 through 1996. The HUD/GSE and HMDA data sets contain individual level data with identifiers for Census tracts. The STF3 contains Census tract data.



As shown in Figure 1, the three data sets were combined to create two new data sets. The first, containing HUD/GSE and STF3 data, was named DATA\_GSE. The second, containing STF3 and HMDA data, was named DATA\_HMDA. In the HUD/GSE and HMDA data sets each individual case includes an identifier for the individual's Census tract. This permits us to match data between the individual case in HUD/GSE or HMDA with the corresponding Census tract data available in STF3. Creating these two data sets allowed us to analyze individual experience, while also accounting for socio-economic factors that might affect mortgage decisions.

### 3-3. Assumptions and Conditions

In the four equations discussed below the following conditions apply:

- i. Only home-purchase loans were considered.
- ii. All types of mortgage loans were included. They are conventional, Federal Housing Authority (FHA), Veterans' Administration (VA), and Farmer's Home Administration (FMHA).
- iii. Only loans for homes that would be owner-occupied as a principal dwelling were included.
- iv. Two loan actions were excluded from the data sets:
  - (1) The loan application was withdrawn by the applicant.
  - (2) The loan file was closed because it was not complete.

Under these conditions, our sample was restricted to home purchase mortgage loans for owner-occupied dwellings, with completed applications that were not withdrawn.

### **3-4. The Equation Structure of the Model**

Here we present the heuristic model we used to generate our results. Several series of equations in our model allow us to address the missing elements of the HMDA data and the Boston Federal Reserve report. The first series addresses "borrower risk," or bad credit, and creates a loan rejection equation that accounts for the probability of rejection because of bad credit.

A second series creates a measure of discrimination, by comparing minorities' actual loan rejection rate to a devised equal-treatment rejection rate. This provides an empirical way to measure discrimination. The third series of equations addresses the issue of saleability on the secondary market, in this case, using data from the two GSEs, Freddie Mac and Fannie Mae.

#### **Estimating Loan Rejection Rate 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 exploit the fact that reasons for loan denial are included, and thus permits us to create a proxy for "bad credit." For rejected applicants, we estimate a logistic equation for a dichotomous variable, equal to one if the rejected applicant was turned down because of "credit history." This equation is estimated for all rejected applicants in an MSA across all five years. Independent variables measure characteristics of the borrower, characteristics of the Census tract, and the year. Although earlier efforts focused on estimation of this equation separately for each year and each race, we soon discovered that the small number of

observations created problems for obtaining convergence of the maximum likelihood estimates. This problem was particularly acute when we narrowed our focus to home mortgage loans only, since in recent years growing proportions of loans in the HMDA data relate to refinancings. We considered it important to focus explicitly on home mortgage loans for owner-occupied dwellings because of the critical effect of such loans on minority homeownership.

The estimated coefficients obtained in the bad credit equation were then used to obtain proxies for bad credit among all loan applicants. These proxies were then included in a loan rejection equation that was estimated separately for each race and ethnicity.

### **Estimating an Equal-Treatment Rejection Rate**

To create a way to measure discrimination, we computed an “equal-treatment” loan rejection rate. By applying the coefficients obtained from the white loan rejection equation to each minority group, we produced a loan rejection rate for each minority as if they were treated like whites. An analogous equal treatment measure is computed by applying the coefficients obtained from each minority loan rejection equation to whites. This produced a loan rejection rate for whites had they been treated like minorities. The measure of discrimination then is the difference between the actual rejection rate and the equal-treatment rejection rate. Either way of measuring equal treatment is acceptable, although the resulting figures will differ.

### **Saleability to the Secondary Market**

To determine the effects of GSE decisions on the measured discrimination, we estimate the loan rejection equal treatment values with and without control for a variable called “probability of loan not being sold on the secondary market to GSEs.” This variable is a proxy for the probability that the loan will not be sold to GSEs. Here are the steps needed to obtain the proxy:

1. A first-time home buyer equation is estimated using Fannie Mae and Freddie Mac data for 1993 through 1996. The dependent variable is a dichotomous variable indicating that the loan applicant was a first-time home buyer. This equation is a function of the characteristics of the borrower, characteristics of the loan, characteristics of the Census tract, and year.

2. The GSE data are used to obtain a predicted value for first-time home buyers for each of the HMDA observations. That is, the coefficients from the first-time home-buyer equation are used to predict the probability of first-time home buyers appearing among loan applicants in the same MSA and within the same race.

3. An equation for the probability that a loan will be sold to GSEs is estimated for all

approved loans. This estimation is based on the combined HMDA and Census data. This is a conditional probability: the probability that a loan is sold to Fannie Mae or Freddie Mac, given that it was approved. Independent variables include: type of lender, characteristics of the loan, characteristics of the Census tract, and year. Excluded are characteristics of the borrower.

4. This conditional probability is combined with an estimate of the origination probability--based on the origination rates by lenders by race in an MSA for the previous year--to obtain an unconditional probability that a loan is not sold to a GSE. This estimate is generated for all loan applicants for each race in a given MSA in a given year (except 1992), and is the proxy used to control for the effects of GSE behavior.

### **3-5. Data Description**

Tables 1 and 2 present the definitions and data sources of variables found in the remaining tables. The four main dependent variables described are bad credit, probability of first-time home buyer, probability of loan 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 the loan, type of loan--FHA, VA, FMHA, or conventional); type of agency (Federal Reserve Board [FRB], Federal Deposit Insurance Corporation [FDIC], Office of Thrift and Supervision [OTS], National Credit Union Association [NCUA], Housing and Urban Development [HUD], or Office of the Comptroller of Currency [OCC]); year; and ratio of amount requested to income.

**Table 1: Definitions of Selected Variables**

For the definitions of all variables used in the 4 logistic regression models, please refer to Table 1-2 in the Technical Analysis Appendix . The detailed descriptions of four dependent variables and other explanatory variables are discussed below.

**BAD\_CR**

A dichotomous variable for the case that credit history is the reason for denial, i.e.,

$$\begin{aligned} \text{BAD\_CR} &= 1 \text{ if } \text{DENIAL1} = 3, \text{ or} \\ &\quad \text{DENIAL2} = 3, \text{ or} \\ &\quad \text{DENIAL3} = 3 \\ &= 0 \text{ otherwise} \end{aligned}$$

**P\_FHO (Probability of First-Time Home Buyer)**

A dichotomous variable for the case that the applicant is a first-time home buyer.

$$\begin{aligned} \text{P\_FHO} &= 1 \text{ if } \text{First-time home buyer} = 1 \\ &= 0 \text{ otherwise} \end{aligned}$$

**P\_SOLD (Probability of Being Sold to GSEs)**

A dichotomous variable for the case that the loan is sold to GSEs.

$$\begin{aligned} \text{P\_SOLD} &= 1 \text{ if } \text{PURCHTYPE} = 1 \text{ or } 3 \text{ (Fannie Mae \& Freddie Mac)} \\ &= 0 \text{ otherwise} \end{aligned}$$

**REJ\_RATE (Probability of Loan Rejection Rate)**

A dichotomous variable for the case that the loan is not accepted.

$$\begin{aligned} \text{REJ\_RATE} &= 1 \text{ if } \text{ACTION} = 3 \\ &= 0 \text{ otherwise} \end{aligned}$$

**GOAL1 (Low- and Moderate-Income Housing Goal)**

The low- and moderate-income goal is defined in terms of purchases of mortgage loans made to families with incomes at or below the area median income (AMI). At least 40 percent of the dwelling units in properties whose mortgages were purchased by the GSEs in 1996 had to be for such families, with this goal rising to 42 percent of 1997-99.

**GOAL2 (Geographically Targeted Housing Goal)**

The geographically targeted goal requires the GSEs to purchase mortgages on properties located in Census tracts within metropolitan areas where either (a) the median income of families does not exceed 90 percent of the AMI or (b) minorities make up 30 percent or more of the residents and the median income of families does not exceed 120 percent of the AMI.

**GOAL3 (Special Affordable Housing Goal)**

The special affordable housing goal is based on income and location. The GSEs are directed to purchase mortgages on units occupied by low-income owners and renters in low-income areas and on units in any area occupied by very low-income owners and renters. The special affordable housing goal is set at 12 percent and 14 percent, respectively, of the total number of dwelling units financed by each GSE's mortgage purchases for 1996 and 1997 through 1999.

**Table 2: Selected Variables from HMDA Codebook**

Agency (AGENCY)

- 1 = Office of the Comptroller of Currency (OCC)
- 2 = Federal Reserve Board (FRB)
- 3 = Federal Deposit Insurance Corporation (FDIC)
- 4 = Office of Thrift and Supervision (OTS)
- 5 = National Credit Union Association (NCUA)
- 7 = Housing and Urban Development (HUD)

Loan Type (LOANTYPE)

- 1 = Conventional (any loan other than FHA, VA, or FMHA) loans
- 2 = FHA-insured (Federal Housing Administration)
- 3 = VA-guaranteed (Veterans Administration)
- 4 = FmHA-insured (Farmers Home Administration)

Reasons for Denial (DENIAL1, DENIAL2, and DENIAL3) Lenders may indicate up to three reasons for denial.

- 1 = Debt-to-Income ratio
- 2 = Employment history
- 3 = Credit history
- 4 = Collateral
- 5 = Insufficient cash
- 6 = Unverifiable information
- 7 = Credit application incomplete
- 8 = Mortgage insurance denied
- 9 = Other

Loan Purpose (LOANPURP)

- 1 = Home purchase
- 2 = Home improvement
- 3 = Refinancing
- 4 = Multifamily dwelling

Action Taken (ACTION)

- 1 = Loan originated
- 2 = Application approved but not accepted
- 3 = Application denied by financial institution
- 4 = Application withdrawn by applicant
- 5 = File closed for incompleteness
- 6 = Loan purchased by your institution

Type of Purchaser (PURCHTYP)

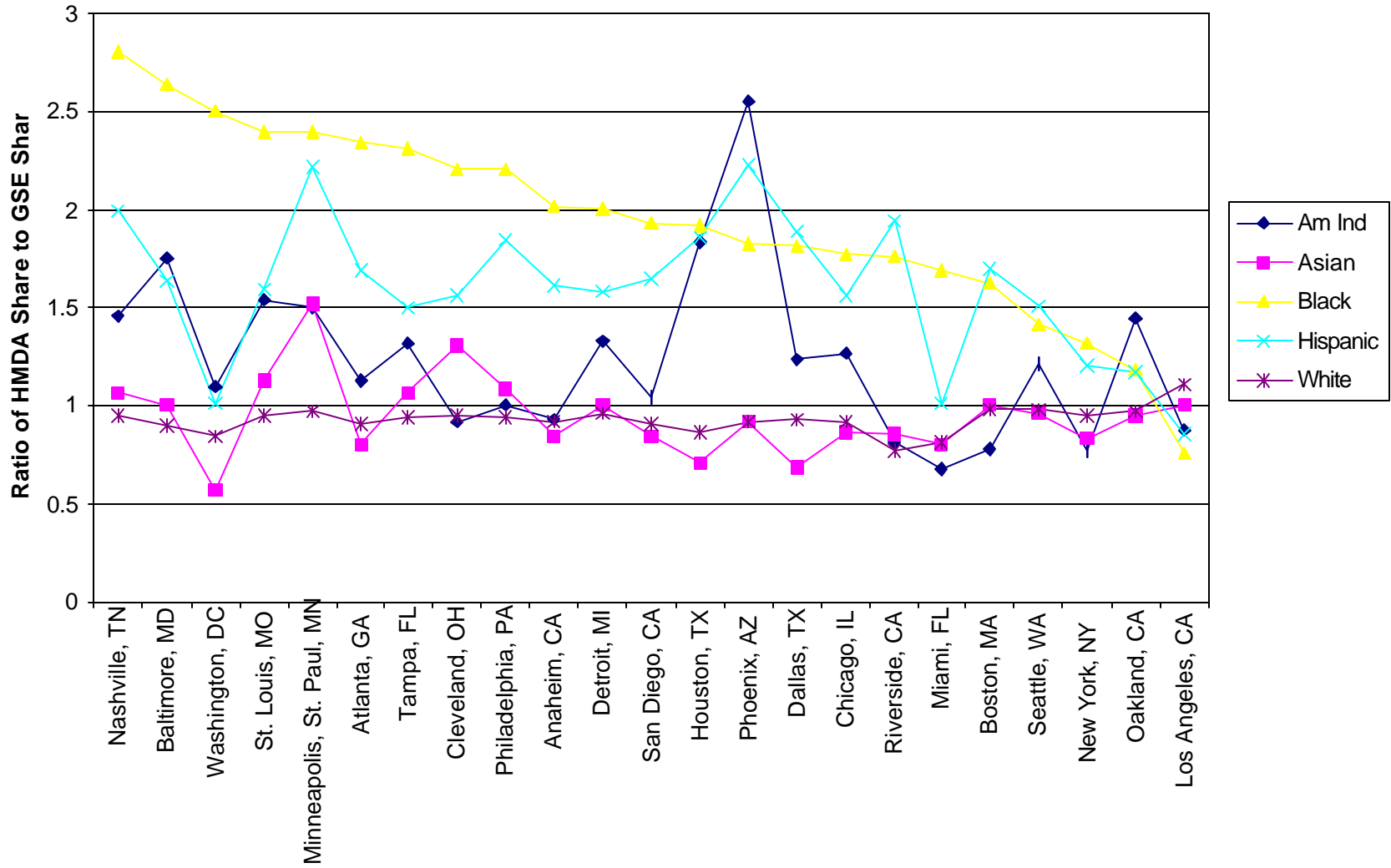
- 0 = loan was originated or was not sold
- 1 = FNMA (Federal National Mortgage Association): Fannie Mae
- 2 = GNMA (Government National Mortgage Association)
- 3 = FHLMC (Federal Home Loan Mortgage Corporation): Freddie Mac
- 4 = FMHA (Farmers Home Administration)
- 5 = Commercial Bank
- 6 = Savings bank or savings association
- 7 = Life Insurance company

Please refer to the appendix for detailed descriptive statistics on: a) the racial distribution of loans in the HMDA data set for each MSA by year; b) the agency distribution of loans by MSA by year; c) the racial distribution of loans sold to Fannie Mae and Freddie Mac by MSA by year; and d) the racial distribution of loans held by GSEs. 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 one percent of the total. Oakland, Los Angeles, Anaheim and New York have the largest percentages of Asian applicants, with upwards of 12 to 19 percent of applicants. Washington, D.C., New York, Baltimore, and Atlanta all had more than 10 percent black applicants, making them the cities with the largest percentages of black loan applicants. Eleven cities had more than 10 percent Hispanic loan applicants: Miami, FL; Riverside, CA; Los Angeles, CA; Houston, TX; Anaheim, CA; San Diego, CA; Chicago, IL; Phoenix, AZ; Oakland, CA; New York, NY; Dallas, TX. The shares range from 10 percent in Dallas to 25 percent in Los Angeles to nearly 70 percent in Miami. While high, these percentages of loan applicants did not always translate into high percentages of loans purchased by GSEs.

It is well established that minority loans are underrepresented in GSE purchases (Bunce and Scheessele, 1996). 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 Nashville, Baltimore, and Washington, D.C., blacks' share of loan applications is 2.5 to almost 3 times that of 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, Arizona, 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, far below the mean for all MSAs. As Figure 2 reveals, however, Asians' share of GSE loans often exceeds their share of all loans, even though in Minneapolis/St. Paul and Cleveland, Ohio, there is a notable underrepresentation of GSE loans among Asians. 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.

Nonetheless, the broad pattern shows wide disparities in the number of black, Hispanic and American Indian loans held by GSEs in comparison 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.

**Figure 2: Minority Underrepresentation Among GSE Loans, 1996**



## **4. The Results**

In the sections below we detail the results obtained from three key aspects of the analysis: a) estimation of the effects of first-time home buyers on secondary market loan sales; b) measurement of discrimination by GSEs; and c) 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.

### **4.1. Loan Rejection Rates With Bad Credit Proxy**

Tables 2-1 to 2-6 report the maximum likelihood estimates of coefficients in a logistic model of bad credit. Factors used 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, Detroit, and Dallas 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, as revealed in Tables 3-1 to 3-23. 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 tables.

### **4.2. Effects of First-time Home Buyers on the Sale of Loans**

Tables 4-1 to 4-23 provide 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 home-buyer loan. These equations are estimated separately by race. The model fit is quite good, with percentages correctly classified ranging from 65 to 100 percent.

Tables 5-1 to 5-23 report the determinants of the probability that a mortgage is sold to a GSE. Variables included are: type of loan; type of lender; loan-to-income ratio, characteristics of the Census tract, and year. Consistently, we find 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, often are not more likely to be sold to these GSEs. The FDIC loans have mixed effects across varying locations and races.

Figure 3 plots the minority/white ratio of the effects of first-time home buyers on the probability that a loan is sold, given that it is actually made. In each entry the plot is the ratio

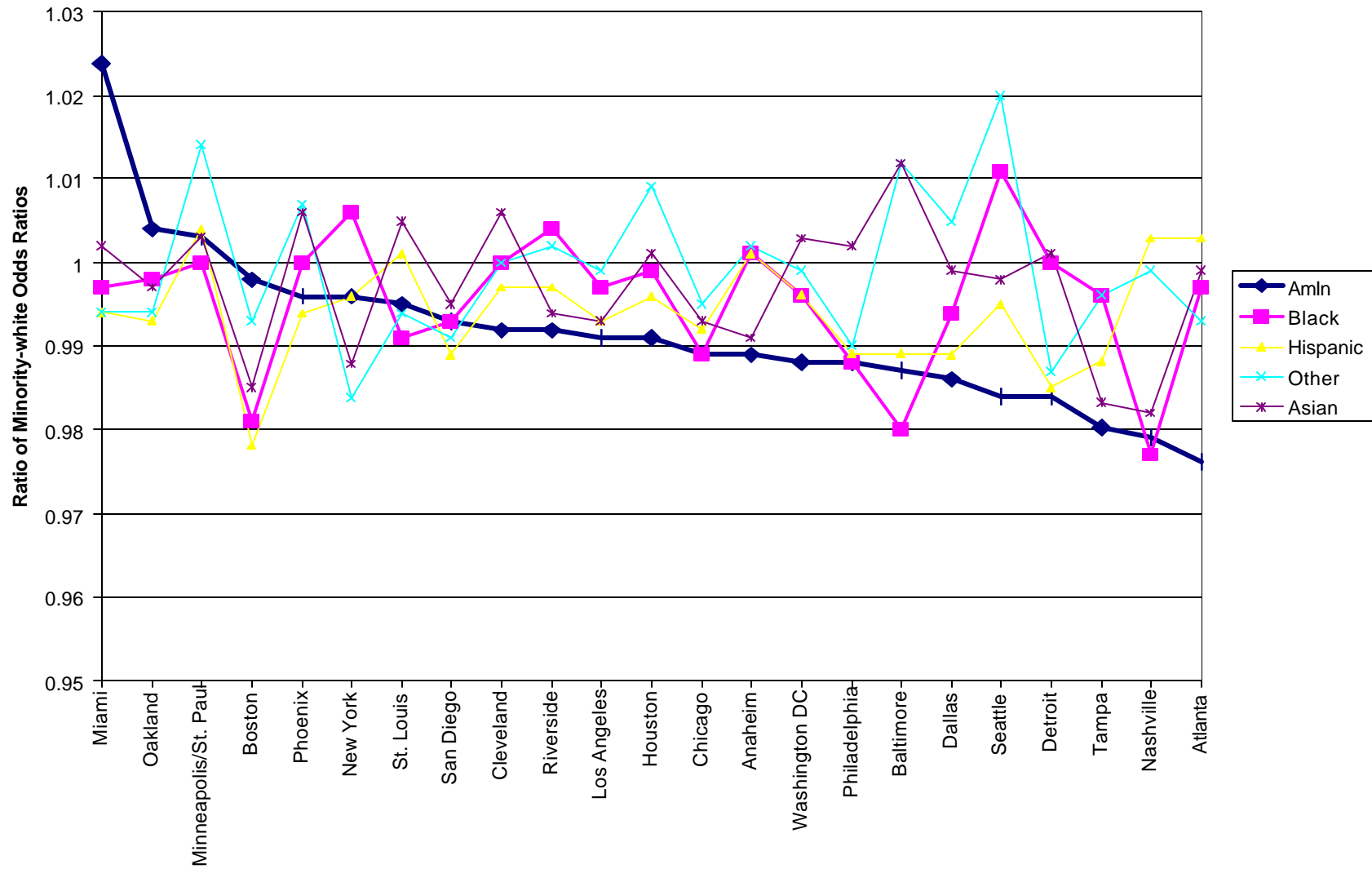
of the minority-to-white odds ratios. When this ratio is less than one, the white effect is larger than the minority effect. When this ratio is greater than one, the minority effect exceeds the white effect. In the vast majority of MSAs the white effect is greater than or equal to the minority effect. In 20 out of 23 MSAs the odds ratio obtained from the American Indian regression is less than or equal to the white odds ratio. In 19 out of 23 MSAs the odds ratio obtained from the black regression is less than or equal to the white odds ratio. In 18 out of 23 MSAs the odds ratio obtained from the Hispanic regression is less than or equal to the white odds ratio. In 15 out of 23 MSAs the odds ratio obtained from the “other” race equation is less than or equal to the white odds ratio. In 13 out 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 vast majority of MSAs--and particularly for American Indians, blacks, and Hispanics--the effects of being a first-time home buyer on the likelihood that an originated loan is sold on the secondary market among minorities are smaller than the effects among whites. This can work in a variety of ways: When the first-time home-buyer effect is to increase the chances that the loan is sold, the positive impact is larger for whites than it is for minorities; when the first-time home-buyer effect is to reduce the chances that the loan is sold, the negative effect is smaller for whites than it is for minorities. And in some instances, the first-time home-buyer effect may be to increase the chances that the loan is sold for whites but to reduce it for minorities.

Figure 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 figure shows that with the exception of the few instances where the American Indian-white ratio of effects is greater than one, the relative effects for other races are almost always larger than the American Indian-white effect. That is to say that American Indian first-time home buyers are more disadvantaged relative to whites than first-time home buyers among other races when it comes to the sale of their loans on the secondary market.

What one must appreciate, however, when viewing the results of Table 6 and the accompanying Figure 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 one, meaning that there is really no fundamental difference in the likelihood that a loan is sold on the secondary market, whether the borrower is a first-time home buyer or not. The figure does show that this small effect is bigger for whites than for minorities. But, it is unlikely that the wide gaps in loan availability between minorities and whites stems principally from the racially differential impacts of being a first-time home buyer on the chances that a loan is sold, once it is originated.

**Figure 3: Effects of First-Time Home Buyer on Probability of Sold, Given Origination**



### 4.3 Discrimination by GSEs?

Tables 7-1 to 7-23 provide estimates of residual discrimination in sale of loans to GSEs. The equations ask, What would be the share of minority loans sold to Fannie Mae and Freddie Mac, had minorities been treated like whites? These computations are performed for each race and each year.

The most straightforward way to interpret the results in these tables is to 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 one or more years in which the equal-treatment 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 than their white 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 one year. The favorable characteristics that predict that the loan would be sold to Fannie Mae or Freddie Mac may also predict that the loan would be sold to these other secondary market participants. In addition, while the underlying equation uses data from four years, the individual years’ estimates are obtained by setting the year dummies equal to one. 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 vs. the secondary market’s decision to purchase a loan. Obviously, lenders must attempt to sell the loan in order 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.

### 4.4 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 account taken of GSE effects. This is done by estimating loan rejection equations for each MSA for each race across the four years. Combining years serves two purposes. First, it enlarges the sample for minorities in each MSA. Second, and more importantly, 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 displayed in Tables 8-1 to 8-23. The two proxies are: bad credit (BAD\_CR2) and the probability that a loan is not sold to a GSE (P\_NOSOLD). Other variables in these regressions include: gender, same-sex applicants, ratio of loan to income, VA or FHA loan, Census tract characteristics, lender type (FRB, FDIC, OTS, NCUA, HUD), and year.

For our final measure of discrimination by GSEs, we consider the effects of a loan 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 about the same as the white coefficients. In New York, the coefficients are all about the same for whites, blacks, Asians, Hispanics and other races. In Washington, D.C., St. Louis, and Miami, the coefficients are of the same order of magnitude for all groups, except Asians, where the coefficient is about half the size of the white coefficient. In some cities, like Phoenix, Boston and San Diego, the American Indian coefficients are measurably larger than those for other groups.

But what is most evident in these tables is the remarkable similarity of absolute sizes of the not-sold 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 as well. To partition the independent impacts of sales to GSEs on the racial disparities in rejection rates, we estimate the model with and without control for GSEs and 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 to begin with.

Tables 9-1 to 9-23 display the results of these computations. Consider the case of New York. Between 1993 and 1996, white loan rejection rates were 12 percent. Loan

rejection rates for blacks were 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 rates 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 that is attributed to the residual difference is

$$(\text{equal-treatment black rejection rate} - \text{black rejection rate}) / (\text{white rejection rate} - \text{black rejection rate})$$

or,  $(.1333 - .1801) / (.1210 - .1801) \times 100 = 79.18\%$ . When account is taken of the GSE decisions (i.e., the probability that the loan is not sold to Fannie Mae or Freddie Mac) the equal treatment probability of rejection becomes .1546. The unexplained gap drops to 43 percent. That is,  $(.1546 - .1801) / (.1210 - .1801) \times 100 = 43.15\%$ . Alternatively, we can consider equal treatment measured from the whites' point of view. The actual white rejection rate is .1210. When whites are treated like blacks, the white rejection rate is .1869. When we also account for GSE decisions, the white rejection rate rises to .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 like whites or when whites are treated like 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 accounts for GSE decisions and the one that does not account for it. The equal-treatment black rejection rate is .1056 when no account is made for GSE decisions, and is .0978 when account is made for GSE decisions. This does result in a nontrivial change in the residual difference--from 72 percent to 81 percent--but a change in the "wrong" direction. That is, in Boston, GSE decisions do not explain the racial gap in loan rejection rates.

The full results of estimation of residual difference with and without control for the probability that a loan is not sold to GSEs are shown in Tables 9-1 to 9-23. The results differ somewhat by race and are discussed in turn under the headings of blacks, Hispanics, Asians, American Indians and others.

### ***The Effects Among Blacks***

Across all 23 MSAs we find that observed rejection rates for blacks exceed the equal-treatment 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 which is not due to observed characteristics of borrowers, lenders, loans, and neighborhoods. The percent of 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 three 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 account of the chances that Fannie Mae or Freddie Mac will not buy the loan, our model estimates that for most MSAs only one-quarter 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 account is made for GSE effects, we find in 20 of the 23 MSAs that the measured discrimination diminishes in non-trivial amounts. In all but Detroit, Houston and Boston, 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 Houston and Boston the differences are very small, amounting to less than 10 percent. The difference in the other direction is less than 10 percent as well, in Dallas, Los Angeles, Philadelphia, and Miami. 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 that which 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. But 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.

The results in Tables 9-1 to 9-23 do not make clear, however, whether GSE decisions "explain" the huge residual gap in lending. Importantly, much of the discriminatory gap remains, even after taking account of 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; in Chicago, 23 percent. By comparison, in Cleveland it is only five percent; in Tampa, less than one percent. The discriminatory gap remains in most of the MSAs, with or without control for GSE effects.

To be sure, in some cities the measured discrimination is sensitive to whether we compute the equal-treatment rejection rates on the black base or the white base—that is, whether we compute the black rejection rate, when blacks are treated like whites, or the white rejection rate, when whites are treated like blacks. Still, it is remarkable that in more than 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 of 1993-1996, the model controlling for GSE effects predicts that if blacks were treated like whites, the black rejection rate would be 19.99 percent. If whites were treated like blacks, the white rejection rate would be 21.09 percent. In other words, 55 percent of the actual gap in rejection rates is due to the unequal treatment of blacks compared to whites; 53 percent of the actual gap in rejection rates is due to the unequal treatment of whites compared to 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 like whites, their rejection rates fall to 21.24 percent, explaining 47 percent of the racial gap. When whites are treated like blacks, their rejection rates rise 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 like whites, their rejection rates rise to 26.73 percent. When whites are treated like blacks, their rejection rates rise to 26.05 percent. The discriminatory differences are -1 percent vs. 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 like whites or by treating whites like blacks. In all but two MSAs (New York and Boston), in measuring discrimination by treating whites like blacks, the residual difference is smaller when we account for GSE effects than when we do not.

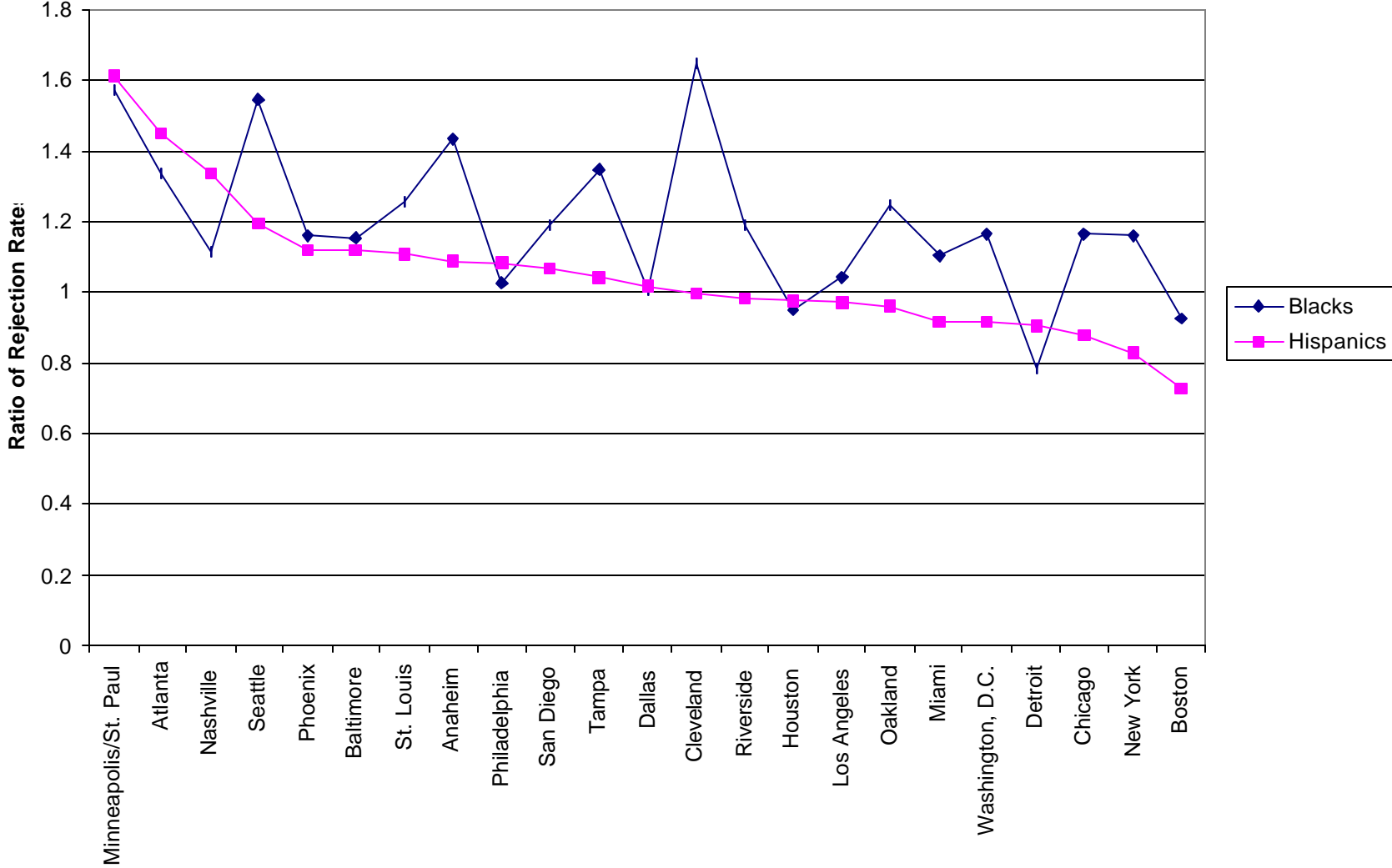
### ***Effects Among Hispanics***

In nearly 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 five percent. Out of the 11 cases in which the equal-treatment rejection rate for Hispanics decreases when account is taken of GSE effects, only three differ by more than 10 percent. Of the 12 cases in which the discriminatory residual is smaller when accounting for GSE effects, only four show a difference of more than 12 percent. In other words, among Hispanics, the GSE effects are much smaller than they are among blacks.

Figure 4 shows the relationship between the GSE effects among blacks and those 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 accounted for, and the ratio is greater than one, the equal-treatment minority rejection rate is underestimated. Or, equivalently, when the ratio is greater than one, failure to account for GSE effects will result in an overestimate of the discriminatory residual. We graph the Hispanic series, ranked from the lowest ratios to the highest ratios and show the comparable black series in the same cities.

The figure 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 figure 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

Figure 4: Ratio of Equal Treatment Rejection Rates With and Without Control for GSE Effects



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 equal-treatment rejection rates would be lower than their actual rejection rates in 14 of the 23 MSAs, and their equal-treatment rejection rates that account for GSE effects are lower in 11 of the 23 MSAs than they are when no account is taken. But these differences arise against a backdrop of extremely small gaps in actual rejection experiences between Asians and whites. Figure 5 plots the ratio of Asian to white rejection rates in 23 MSAs. When this ratio is greater than one, Asians are disadvantaged. When this ratio is less than one, Asians are advantaged. Figure 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 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 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 upward the measure of discrimination. 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 had they been treated like 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

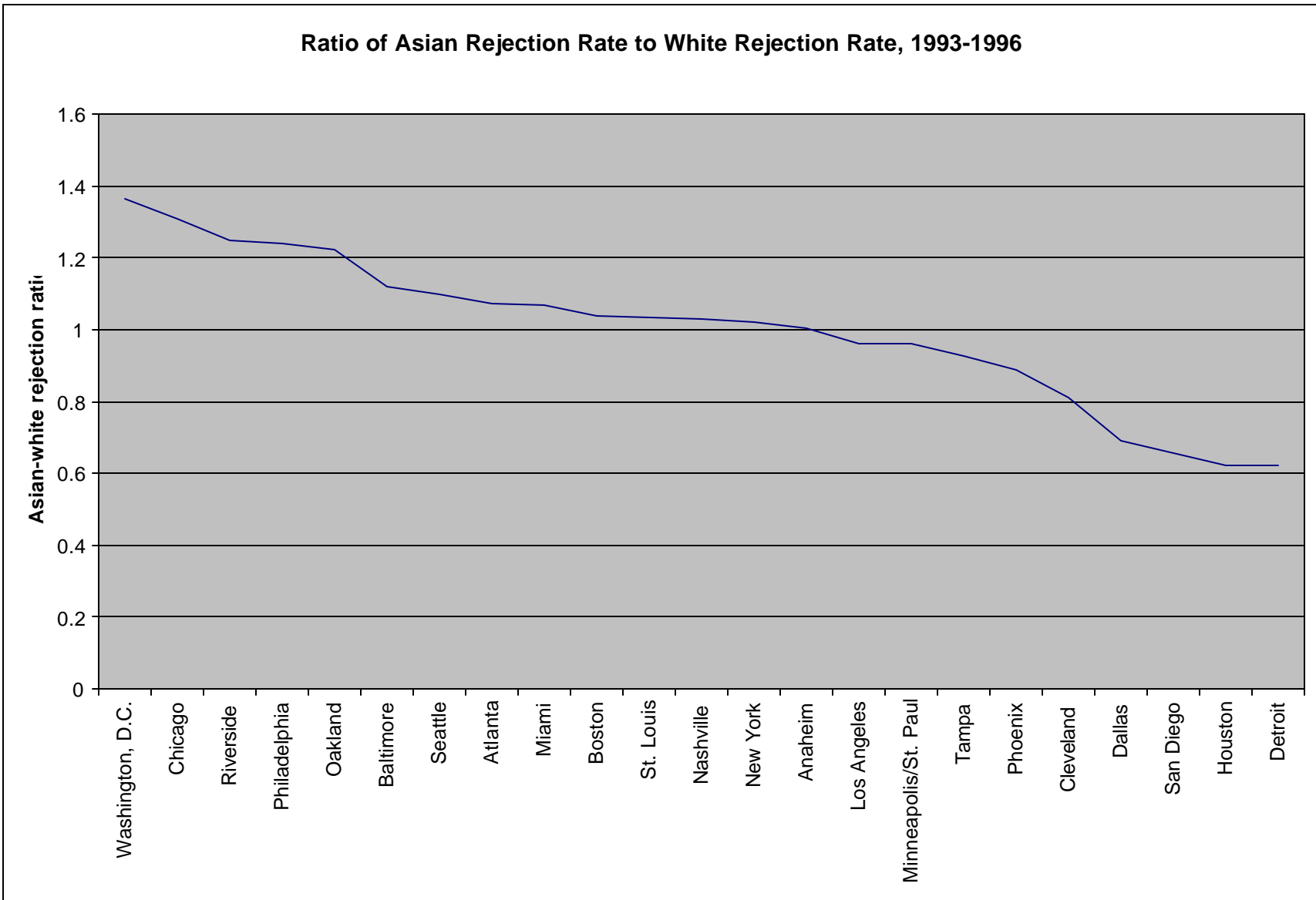


Figure 5

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.

### ***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 like 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 three percentage points lower in Minneapolis/St. Paul (13 percent vs. 16.6 percent); in Boston they would be three percentage points higher (12.97 percent vs. 9.78 percent); and in New York, they would be less than one percentage point lower (14.71 percent vs. 15.46 percent).

The chart below sums up the results. If the equal-treatment rejection rate in Tables 10-1 to 10-23 in the Appendix is higher than the equal-treatment rejection rate that accounts for discrimination by GSEs, then we 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, then we conclude that GSE discrimination does not explain racial lending gaps.

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 where there is no such finding as there are ones where the effect seems to hold. But 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.

***Does GSE Discrimination Explain Racial Gaps in Loan Rejection Rates?***

	<b>Blacks</b>	<b>Asians</b>	<b>Hispanics</b>	<b>American Indians</b>	<b>Other</b>
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
MSP	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	YES	NO
Seattle	YES	YES	YES	NO	YES
Tampa	YES	NO	NO	NO	YES
Wash. D.C.	YES	YES	NO	NO	YES

**5. Conclusion**

On its face, the lender's 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 won't sell on the secondary market systematically increases the probability that a loan 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 minorities have lower loan sales 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--while statistically significant--is small. 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 (but 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 are lower, for Hispanics are lower, for American Indians are higher and for other races are 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 see this in another light, we have computed the ratio of the equal-treatment rejection rates with and without control for GSE disparities. 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 one indicates that discrimination at the secondary market level contributes to discrimination in loan-rejection rates. A ratio less than or equal to one indicates that discrimination in sales of loans to GSEs cannot be the cause of lending disparities.

The following figures reveal that it is not possible to draw a conclusion that holds across all MSAs for all minority groups. The first figure does show that in most instances the ratio is greater than one for blacks, but there are several MSAs for which the ratio is very close to one or slightly less than one. Among Asians, the ratio is nearly equal to one across all MSAs, but only because it is above one in about half and below one in another half. Among American Indians the ratio is equal to or below one in a large share of the MSAs, but the few MSAs where the ratio is substantially above one causes the mean for all of the MSAs to rise to 1.098. Among Hispanics the mean for all MSAs is visibly below one, at .96, with a handful of

MSAs registering values above one. For other races, the ratio is visibly close to one in all but a few cases, where the ratio is substantially above one, causing the mean to rise to about 1.118.

We conclude from this summary of the residual discrimination analysis that one 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 over all for blacks and indeed are higher among Hispanics. This finding is hardly that needed to absolve lenders of culpability in racial-lending disparities.

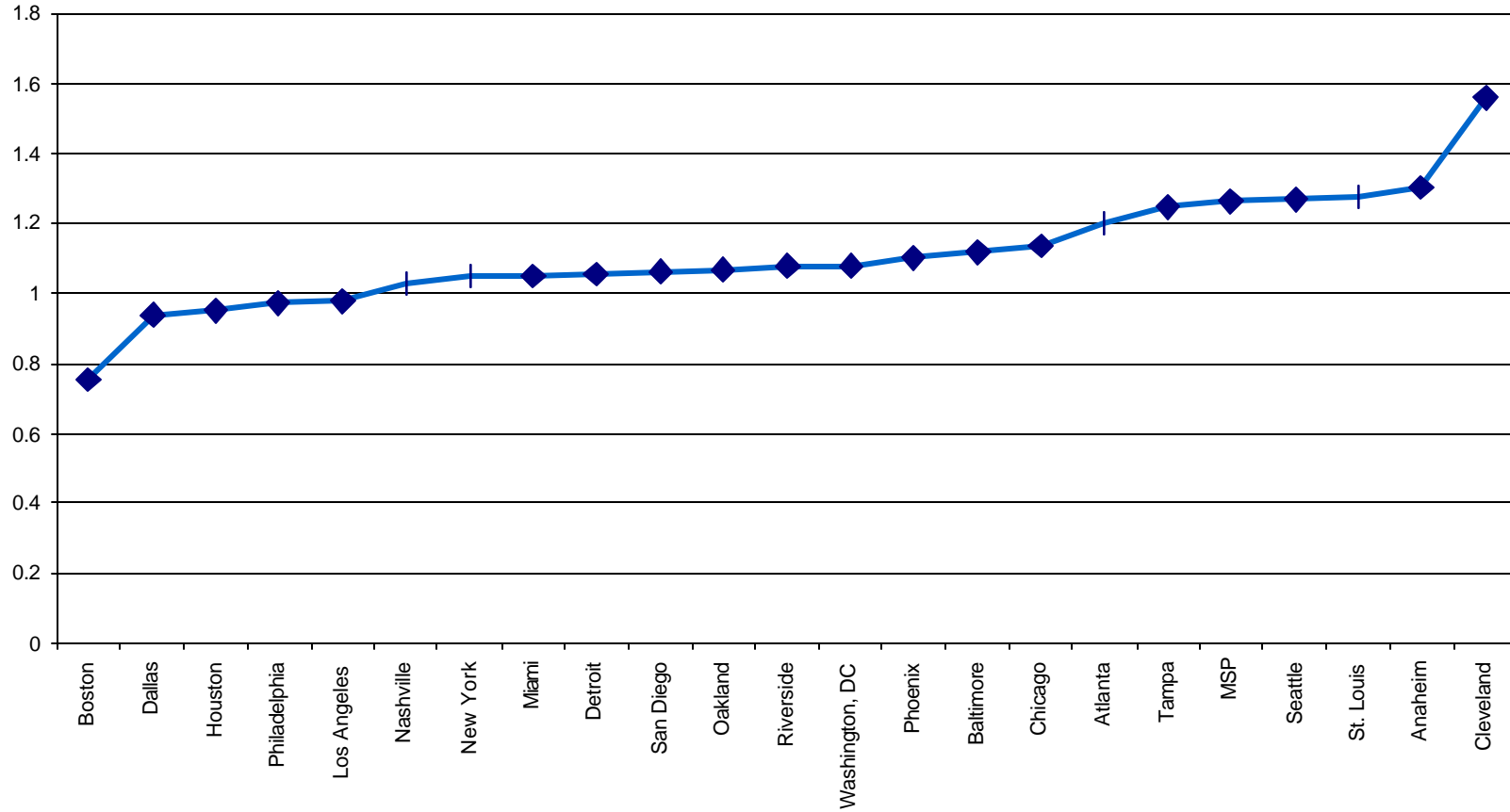
One finding emerges consistently about discrimination. No matter how one computes the discriminatory residual, and whether or not account is taken for GSE decisions, a nontrivial "unexplained residual" difference in loan-rejection rates between blacks and whites remains. In New York City, the lowest computed black discriminatory residual is 43 percent; in Boston, it is 72 percent; in Minneapolis it is 32 percent. These results are on the same order of magnitude in Boston and Minneapolis when the computation is performed in an alternative way—when whites are treated like blacks, rather than blacks like whites. In New York, we estimate that when whites are treated like 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.

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 finding for other races are particularly idiosyncratic with respect to location.

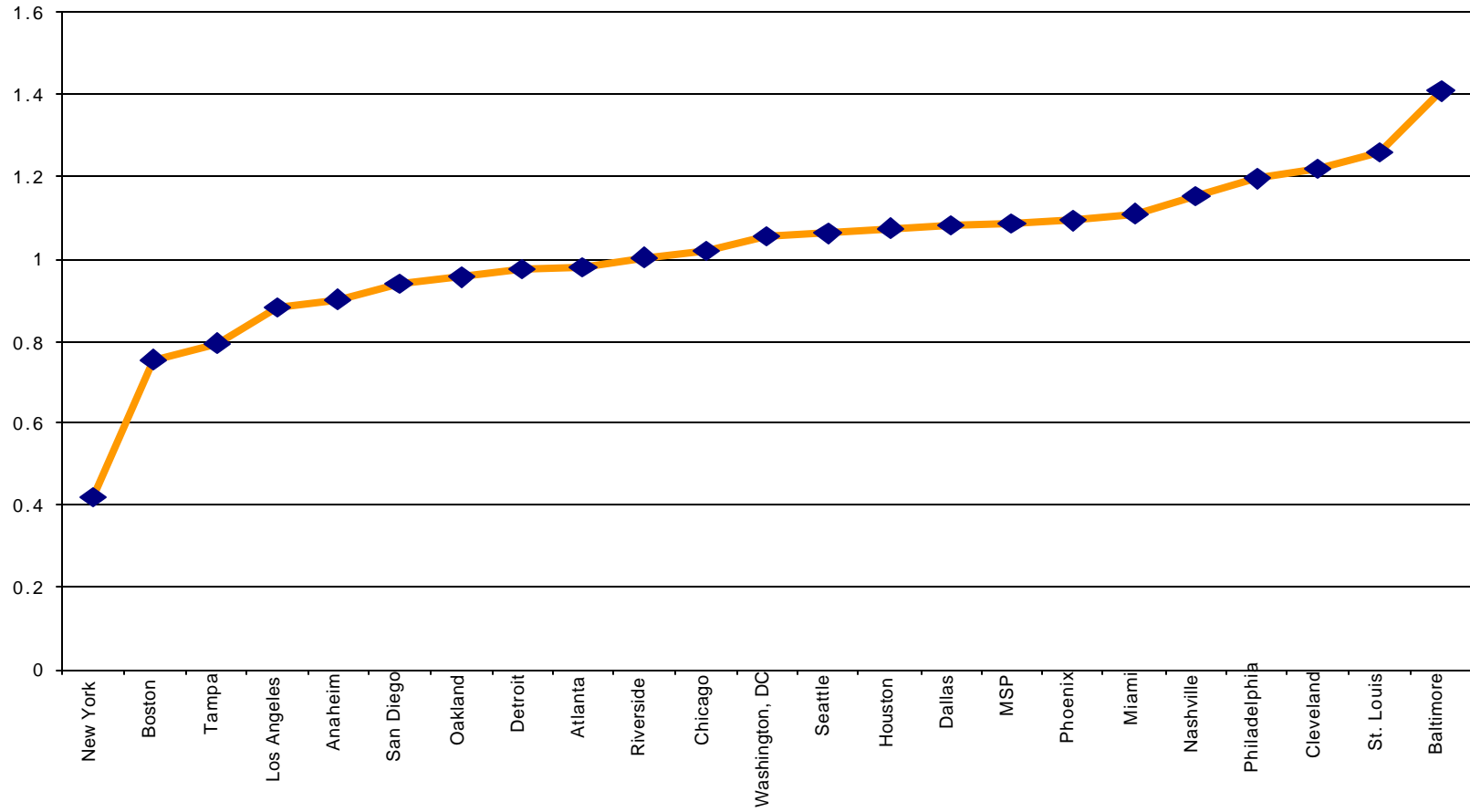
Our conclusion from the study, as it applies to public policy, therefore, is that extraordinary model sophistication and estimation upholds the finding of wide unexplained disparities in loan-rejection rates between black and white applicants for home mortgage loans in HMDA data. While these unexplained disparities theoretically can be explained 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.

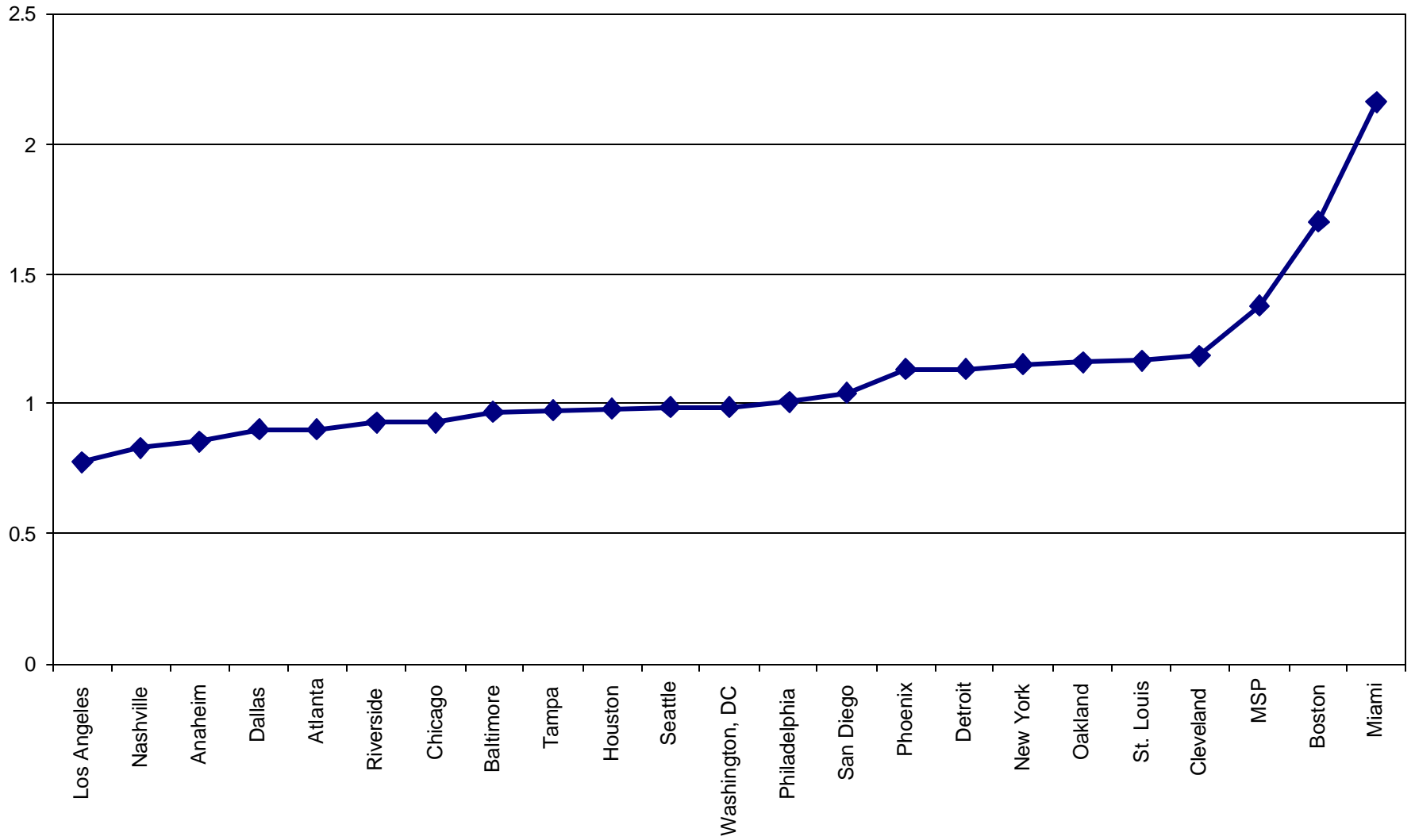
Ratio of Equal-Treatment Rejection Rates, Blacks (Mean = 1.11)



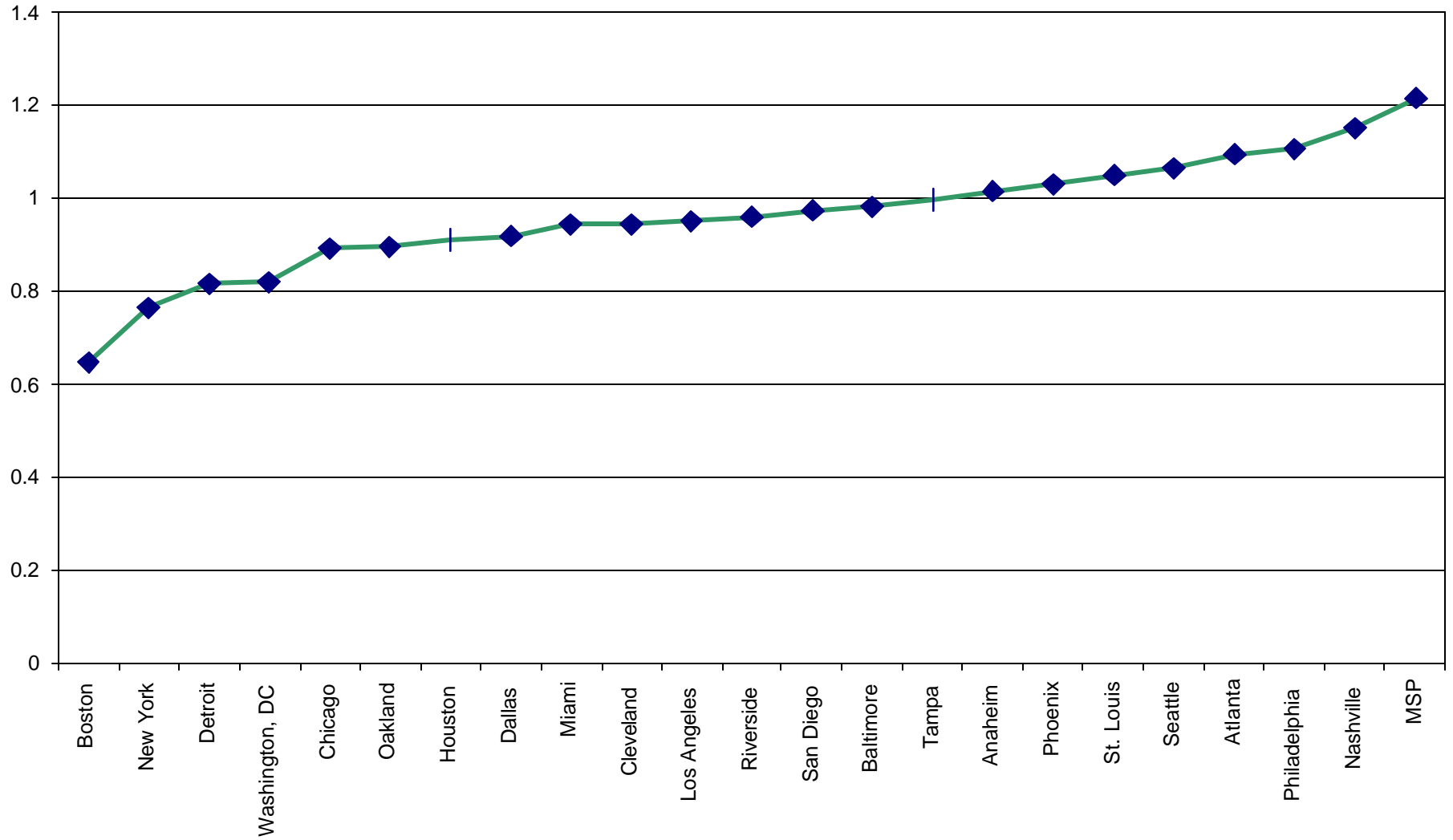
Ratio of Equal-Treatment Rejection Rates, Asians (Mean = 1.018)



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



Ratio of Equal-Treatment Rejection Rates, Hispanics (Mean = .96)



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

