Mortgage Lending Decisions and Racial/Ethnic Bias in Boston

Data from 1990 HMDA Report

Qianhui Guo, Jillian Pflugrath Bass, Ying Xue
ECON 5300

Professor Hiedemann
March 13th, 2019

1. Introduction

Owning a home is a key fixture of the American dream. More than just a symbol, owning a home is an important tool for building wealth. Homeownership does involve financial risk, but even under less than ideal market conditions, there is strong evidence to support the association between owning a home and accumulating wealth. As Herbert et al (2013) explain, "homeownership continues to represent an important opportunity for individuals and families of limited means to accumulate wealth." Amortizing mortgages to finance a home results in forced savings since a part of the payments each month go toward principal reduction. Homes also generally appreciate in value over time. According to the Federal Housing Finance Agency, in the US between 1975 and 2012, the compound annual growth rate in house prices exceeded inflation by 0.8 percentage points. Over 30 years, that compound rate amounts to a real gain of about 26 percent in the overall house value. Goodman and Mayer (2018) examined the investment performance of homes using data from 2002 to 2018 and found that even during a period including the Great Recession, "homeownership is quite favorable compared to alternative investments" (p.32).

According to the U.S. Census Bureau's homeownership statistics, in the fourth quarter of 2018, the rate of homeownership across the United States was 64.8%. But separated by race/ethnicity, the rate of homeownership was 73.6% for Whites, 46.9% for Hispanics, and 42.9% for Blacks. There are many factors contributing to this disparity that must be examined. Our research focuses on racial bias by mortgage lenders. Specifically, using data from the Boston Metropolitan area, if applicants are otherwise equal, are non-white mortgage applicants less likely to be approved for a mortgage? Using maximum likelihood estimation (MLE), we estimate both logit and probit equations to compare the likelihood of for mortgage loan applications. Using our logit and probit models, we also calculate predicted probabilities for 12 prototypical applicants, and we estimate odds ratios with our logit model. Based on our analysis, when the only difference is race/ethnicity, white applicants are consistently more likely to be approved.

2. Econometric Model and Estimation Method

In this research, as the outcome of the mortgage lender's decision is binary, either approve or not approve, to investigate whether the race/ethnicity of an applicant impacts a mortgage lender's decision, we use a probit and logistic regression rather than the simple linear regression and use MLE to fit the model, then we calculate predicted probability to compare among three race/ethnicity groups: White, Black, and Hispanic. Furthermore, to control for the impact of other variables on race, we estimate the predicted probabilities for 12 prototypical applicants when all other numeric variables are set at their means, conditional on race/ethnicity, marital status, and whether credit history meets guidelines. Besides, to measure the strength of the association between each independent variable and mortgage loan approval, we also calculate odds ratios in logistic model for both the dummy and continuous random variables. `

Our estimated equations include two numeric factors used by lenders in their decision-making process: the loan amount as a percent of total purchase price (loan to value) and the amount of other financial obligations as a percent of total income (other obligations). We use dummy variables for the following categorical variables: meeting credit history guidelines (meet guidelines), marital status, and race/ethnicity. The excluded variable for "meet guidelines" is not meeting credit history guidelines, for race/ethnicity is white, and for marital status is single. Marital status can be an important factor in a lenders' decision, because married applicants generally have higher repayment ability and may be more favorable to lenders as two individuals are responsible for the loan. For example, if a husband is sued for an unpaid debt, the wife's wages could be garnished to pay the debt. Whether the applicant's credit history meets the guidelines is also an important indicator because lenders face higher possibilities of default if they issue loans to applicants with poor credit history. Race/ethnicity is included to compare the gap of loan approved probability among racial/ethnicity groups. We exclude gender because it does not offer meaning for married applicants, because both spouses share responsibility for the loan. And given that same-sex marriage was not legal in 1990, we know that married applicants in our sample represent both a male and a female. By including these explanatory variables, our research attempts

to control for all the relevant information related to the mortgage lending decision, in order to examine the role of race/ethnicity.

3.Data

3.1 Data Sources

We use data from the 1990 Home Mortgage Disclosure Act (HMDA) report, with individual observations amounting to 1990, including all applications for conventional mortgage loans made by Blacks and Hispanics in 1990 and a random sample of applications made by Whites. HMDA data indicate whether an applicant's mortgage application was approved and provide several demographic characteristics corresponding to the lending decision.

3.2 Variables, Measurement, and Selection Criteria

For the Marital Status variable, we remove all observations with the unreasonable value ".". For the dummy variable "meet guideline", we remove all observations with values other than "1" or "0". For ease of interpretation, we converted the "loan to value" ratio from a decimal value to a percent value by multiplying by 100. We also removed all "loan to value" observations with values greater than 100%. We reason that observations greater than 100% could skew the results, because it is less common for lenders to approve mortgage applications where the loan amount is greater than the purchase price.

3.3 Descriptive Statistics

After making the aforementioned adjustments, our sample size is 1,937. Black and Hispanic applicants account for about 15% of the total observations. As shown in Table 1, the mean of "loan to value" for our selected sample is 76.08%, ranging from 2% to 100%, indicating a large range of down payment amounts across mortgage loan applicants. The average of "other obligation" is 32.37%, ranging from 0% to 95%, indicating there are both new and aggressive borrowers among the applicants. In the sample, 91.4% of the applicants have credit histories that meet the guidelines. Overall, 87.9% of the mortgage loan applications in our sample are approved.

As shown in Table 2, Table 3, and Table 4, on average, Black and Hispanics have higher "loan to value" and higher "other obligation" than White applicants. The approval rate for White applicants is 24.3 percentage points higher than Black applicants and 13.1 percentage points higher than Hispanic applicants. White applicants in this sample also have a better credit history, with 93.9% meeting credit history guidelines--21.5 percentage points higher than Black applicants and 7.4 percentage points higher than Hispanic applicants.

4. Results

We examine whether race/ethnicity is associated with the outcome of a mortgage loan application by estimating logistic and probit models, shown in Table 5 and Table 7 respectively. The dependent variable in each specification is the approval for mortgage loans application, and the independent variables include the ratio of loan amount to purchase price, the proportion of other obligations in total income, marital status, race/ethnicity, as well as whether credit history meets guidelines. Table 6 and Table 8 show the predicted probability based on the logistic model and probit model, respectively, for 12 prototypical applicants, conditional on race/ethnicity, marital status, and meeting credit history guidelines.

4.1 Logistic Model, Odds Ratio, and Predicted Probability

Table 5 displays the coefficients and odds ratio associated with our logistic regression model. From the result, we conclude that there is a premium for White applicants when applying for a mortgage loan. Statistically significant at the 1% level, Black and Hispanic applicants are both less likely than White applicants to be approved for a mortgage.

Controlling for marital status, the ratio of loan amount to purchase price, the proportion of other obligations in total income, and whether credit history guidelines are met, both Black and Hispanic applicants are less likely than White applicants to be approved for a mortgage. This result is significant are the 1% level. The estimated odds of mortgage loan approval are 58.1% less for Black applicants and 57.7% less for Hispanic applicants than among white applicants (odds ratio for black = 0.419; odds ratio for Hispanic = 0.423), while the estimated odds of mortgage loan approved is slightly different between Hispanic applicants and Black applicants. The likelihood of approval varied by other characteristics, such as marital status credit history meeting guidelines, the ratio of loan to value and the

proportion of other obligations. As expected, relative to unmarried applicants, married applicants have a greater likelihood of approval, significant at the 1% level. Meeting credit history guidelines is the most important factor for loan approval. The estimated odds of receiving a loan approved is 43.2 times greater among applicants who met the guidelines than among those who did not. Moreover, both the ratio of loan to value and the proportion of other obligations lead to a decrease in loans approved, statistically significant at 5% level and 1% level respectively. The estimated odds of receiving a loan approved for an applicant is 1.6% lower than the odds for another applicant whose ratio of loan to value is one percentage lower, after holding all other variables constant.

Table 6 presents the predicted probability for 12 prototypical applicants based on our logistic regression model, conditional on race/ethnicity, marital status, and whether credit history meets guidelines, that an applicant with an average ratio of loan to value (76.075%) and average proportion of other obligations in income (32.366%) get approved from the lenders. To control for marital status and the condition that whether an applicant's credit history meet guidelines, we separate the applicants into groups to compare the approval probability of race/ethnicity when those applicants meet the same condition in marital status and credit history status. In each group, there is consistently a premium for White applicants, regardless of whether they are married or their credit history meets the guidelines, comparing to the Black and Hispanic applicants. When all numeric variables are set at their means, the predicted probability of receiving an approved loan for a married White applicant with a good credit history is 96.0%, about 5 percentage points greater than that of a Black or Hispanic applicant. There is a huge difference of loan approval between race/ethnicity when applicants' credit records don't meet guidelines. When all numeric variables are set at their means, the predicted probability of receiving an approved loan for a married White applicant without a good credit history is 35.6%, while in the same condition the predicted probability of Black and Hispanic applicants are only 18.8% and 19.0%, respectively.

4.2 Probit Model and Predicted Probability

Table 7 exhibits the coefficients associated with our probit regression model. The race/ethnicity appears to influence the approval for mortgage loans, which is statistically significant at 1% level. The result shows that, controlling for other variables, Black and

Hispanic applicants are significantly less likely to receive approved loans than White applicants. Marital status and meeting the credit history guideline also have statistically significant relationships with mortgage loan approval at the 1% level. An applicant can benefit from his/her married status and good credit history, and thus he/she is more likely to receive their loan approved. Higher value of the ratio of loan to purchase price and the proportion of other obligations lead to a lower approval for mortgage loans, statistically significant at 5% level and 1% level respectively. All of these results are consistent with our finding in our logistic regression model as well.

Table 8 reports the predicted probability based on our probit regression model for 12 prototypical applicants. It's also conditional on race/ethnicity, marital status and whether applicant's credit history meets guidelines and in the meanwhile all other numeric are also set at their means(loan to value = 76.075% and other obligation = 32.366%) , to find out the relationship between race/ethnicity and the approval for mortgage loans when applicants meet the same condition in marital status as well as whether guidelines are met by their credit history. Although a married applicant with a good credit history leads to the highest predicted probability of loan approved from our result, there is still some difference between White and other race/ethnicity. In this situation, 96.1% of white applicant get approved for their applications, while the predicted probability of Black and Hispanic applicants is 90.4% and 90.5%, respectively, when all other variables are set at their means. However, if the applicant doesn't have a good credit history, it is shown that the gap between races becomes much bigger. Specifically, the predicted probability of a married White applicant is 34.0%, around 14.5 percentage points greater than a married Black or Hispanic applicants. An unmarried White person has about 12.0 percentage points premium compared with an unmarried Black or Hispanic applicant facing the same situation.

4.3 Consistency of Logistic and Probit Model

From both logistic and probit model, we can reach a consistent conclusion that race/ethnicity has a statistically significant relationship with the approval for mortgage loans at 1% level and White applicants are always more likely to receive approved loans than Black or Hispanic applicants.

5. Conclusion

5.1 Limitations

These results are limited to the Boston metro area and cannot be used to accurately make claims about patterns for the United States as a whole. The disparities could be greater in less-diverse areas or lesser in more-diverse areas. Also because our data is cross-sectional, we are limited by only observing a snapshot in time of the loan applicants. People who were denied may be approved by another bank or later in their life. There could also be other implicit factors impacting lenders' decisions that are not accounted for in our models. Our predicted probabilities allow us to compare prototypical applicants. But because these prototypes rely on the mean of numeric independent variables, it does not necessarily represent any real applicants from our sample, and only general comparisons can be made.

5.2 Results, Implications, and Future Research

The results of our research show that race/ethnicity has an impact on the approval of mortgage loans, and suggests a consistent racial bias of mortgage lending approvals in the Boston Metropolitan Area. It's clear that meeting credit history meets guidelines is a key factor in the mortgage lending decision, but out of applicants whose credit histories don't meet the guidelines, when all other numeric variables are set at means, white applicants have greater predicted probability of being approved. In many situations, lenders have discretion, and our estimations show that they are more likely to take a chance on white applicants. While it's possible that there is some conscious (or explicit) racial bias, it is likely that much of this disparity comes from unconscious bias. The University of California, San Francisco's (UCSF) Office of Diversity and Outreach explains that "Unconscious biases are social stereotypes about certain groups of people that individuals form outside their own conscious awareness." This type of bias is much more prevalent and insidious than conscious prejudice. The lenders are likely unaware of their bias, and their implicit bias may even go against their conscious values. Although the Fair Housing Act has been in place since 1968, a law alone cannot stop unconscious bias. In addition to the law, there must be procedures for analyzing applications without knowing the race/ethnicity of an applicant. Name and race/ethnicity should be excluded from the assessment. Without these policies in

place, many minorities may never own a home, missing out on an opportunity to build wealth and pass on wealth to their families, perpetuating disadvantage for generations to come.

UCSF Office of Diversity and Outreach also notes that unconscious or conscious biases can exist toward any social group: "gender, gender identity, physical abilities, religion, sexual orientation, weight, and many other characteristics are subject to bias." Further research must be done to examine implicit bias in mortgage lending decisions affecting other minority or stigmatized social groups, including but not limited to sexual minorities, disabled people, and veterans.

References

Goodman, Laurie S. and Christopher Mayer. "Homeownership and the American Dream." Journal of Economic Perspectives 32, no. 1 (Winter 2018): Pages 31–58. https://www.urban.org/sites/default/files/publication/96221/homeownership_and_the_american_dream_0.pdf.

Herbert, Christopher E., Daniel T. McCue, and Rocio Sanchez-Moyano. "Is Homeownership Still an Effective Means of Building Wealth for Low-income and Minority Households? (Was it Ever?)." Harvard University, Joint Center for Housing Studies. (September 2013).

United States Census Bureau. "Quarterly Residential Vacancies and Homeownership, Fourth Quarter 2018." February 28, 2019. https://www.census.gov/housing/hvs/files/currenthvspress.pdf

University of California, San Francisco Office of Diversity and Outreach. "Unconscious Bias." Accessed March 10, 2019. https://diversity.ucsf.edu/resources/unconscious-bias

Contributions

Qianhui Guo: Data analysis and result interpretation
Ying Xue: Sample selection criteria, model and estimation method, and data
Jillian Pflugrath Bass: Intro, conclusion, and editing

All teammates worked together on revising the paper.

```
Table 1. Descriptive Statistics of All Applicants
==================================================================
Statistic          N    Mean   St. Dev.  Min  Pctl(25) Pctl(75)  Max
------------------------------------------------------------------
Loan to Value    1,937 76.075  16.763   2.000  69.700   89.800  100.000
Other Obligation 1,937 32.366   8.247   0.000  28.000   37.000   95.000
BLACK            1,937  0.099   0.299     0       0        0        1
HISPANIC         1,937  0.054   0.225     0       0        0        1
Meet Guidelines  1,937  0.914   0.281     0       1        1        1
APPROVE          1,937  0.879   0.327     0       1        1        1
------------------------------------------------------------------
```

```
Table 2. Descriptive Statistics of White applicants
==================================================================
Statistic          N    Mean   St. Dev.  Min  Pctl(25) Pctl(75)  Max
------------------------------------------------------------------
Loan to Value    1,641 74.782  17.165   2.000  67.700   89.100  100.000
Other Obligation 1,641 31.994   8.183   0.000  27.600   36.500   95.000
Meet Guidelines  1,641  0.939   0.239     0       1        1        1
APPROVE          1,641  0.910   0.287     0       1        1        1
------------------------------------------------------------------
```

```
Table 3. Descriptive Statistics of Black applicants
==================================================================
Statistic         N    Mean   St. Dev.   Min   Pctl(25) Pctl(75)  Max
------------------------------------------------------------------
Loan to Value    192 82.890  12.632   28.986  80.000   90.227  100.000
Other Obligation 192 35.028   8.131    5.600  31.000   38.900   63.000
Meet Guidelines  192  0.724   0.448      0       0        1        1
APPROVE          192  0.667   0.473      0       0        1        1
------------------------------------------------------------------
```

```
Table 4. Descriptive Statistics of Hispanic applicants
==================================================================
Statistic         N    Mean   St. Dev.   Min   Pctl(25) Pctl(75)  Max
------------------------------------------------------------------
Loan to Value    104 83.909  10.919   40.000  80.000   90.300  100.000
Other Obligation 104 33.315   8.558   14.600  29.000   38.050   62.000
Meet Guidelines  104  0.865   0.343      0       1        1        1
APPROVE          104  0.779   0.417      0       1        1        1
------------------------------------------------------------------
```

Table 5. Logit Models of Mortgage Loan Approval

```
===================================================
                        Dependent variable:
                -------------------------------------------------
                                APPROVE

                  Parameter Estimates      Odds Ratio
-------------------------------------------------------------------
Meet Guidelines         3.766***             43.227
                        (0.221)

Loan to Value(%)        -0.016**              0.984
                        (0.007)

Other Obligation(%)     -0.034***             0.967
                        (0.011)

BLACK                   -0.869***             0.419
                        (0.243)

HISPANIC                -0.860***             0.423
                        (0.323)

MARRIED                 0.482***              1.619
                        (0.185)

Constant                1.233*                3.431
                        (0.685)

-------------------------------------------------------------------
Observations                      1,937
Log Likelihood                   -462.546
Akaike Inf. Crit.                 939.091
===================================================
```

Note:
*p<0.1; **p<0.05; ***p<0.01
Numbers in () are standard errors

Table 6. Predicted Probabilities for Mortgage Loan Application Approval from Logit model

	Mortgage Loan Application Approval		
	White	Black	Hispanic
Married Meet guidelines	*0.960*	0.909	0.910
Unmarried Meet guidelines	*0.937*	0.861	0.862
Married Does not meet guidelines	*0.356*	0.188	0.190
Unmarried Does not meet guidelines	*0.255*	0.125	0.126

Table 7. Probit Models of Mortgage Loan Approval
==
                        Dependent variable:

                              APPROVE

Meet Guidelines   2.169***
                              (0.123)

Loan to value(%)   -0.007**
                              (0.003)

Other Obligation(%)   -0.016***
                              (0.005)

BLACK   -0.450***
                              (0.128)

HISPANIC   -0.444***
                              (0.169)

MARRIED   0.239***
                              (0.092)

Constant   0.435
                              (0.337)

Observations   1,937
Log Likelihood   -462.491
Akaike Inf. Crit.   938.982
==
Note:
*p<0.1; **p<0.05; ***p<0.01
Numbers in () are standard errors

Table 8. Predicted Probabilities for Mortgage Loan Application Approval from Probit model

	Mortgage Loan Application Approval		
	White	Black	Hispanic
Married Meet guidelines	*0.961*	0.904	0.905
Unmarried Meet guidelines	*0.936*	0.857	0.859
Married Does not meet guidelines	*0.340*	0.194	0.196
Unmarried Does not meet guidelines	*0.258*	0.135	0.137