The Role of Race and Ethnicity in Massachusetts Mortgage Markets

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Abstract

This study uses a binomial logit model to examine the influence of socioeconomic and demographic factors on mortgage market outcomes. Analyzing the HMDA 2022 dataset of mortgage applications, we investigate the impact of income, loan amount, race, ethnicity, property type, and gender on the probability of mortgage approval. The results indicate that income and loan amount significantly affect mortgage application outcomes, emphasizing the importance of financial ability. Additionally, race and ethnicity variables play a crucial role, with Black and Asian applicants experiencing negative and positive effects, respectively, on mortgage acceptance probabilities. Ethnicity as a categorical variable also significantly impacts the relevance of sociocultural factors in lending decisions. These findings shed light on the complex interplay between individual attributes and lending decisions in mortgage markets. The study underscores the need for equitable lending practices and provides valuable insights for policymakers, lenders, and stakeholders in mortgage lending.

Keywords: Mortgage markets, discrimination, race and ethnicity, HMDA

The Role of Race and Ethnicity in Massachusetts Mortgage Markets

Fuelled by discoveries of discriminatory practices in housing markets, like redlining, researchers are now scrutinizing the role of race and ethnicity in shaping access to the housing market, particularly mortgages (BPDA Research Division, 2023). This heightened awareness builds upon prior research identifying a link between race and access to mortgage options. For instance, Cherian (2014) utilized the Home Mortgage Disclosure Act (HMDA) data from locations outside Massachusetts to demonstrate statistically significant correlations between an applicant's race and the type of mortgage they were offered. These findings suggest that applicants of color may be systematically steered towards less favorable loan terms, hindering their ability to achieve homeownership to build generational wealth (Pfeffer & Killewald, 2019) and secure mortgages with more favorable interest rates.

Further research is necessary to verify these initial findings and investigate the underlying mechanisms driving these disparities in Massachusetts. Understanding potential discrimination is crucial for crafting effective policy solutions for promoting fair home financing (mortgage) access across all racial and ethnic demographics. We intend to replicate a scenario of Cherian (2014) in Massachusetts and answer the question:

How did race and ethnicity impact Massachusetts mortgage markets in 2022?

Data

The Home Mortgage Disclosure Act (HMDA) requires lenders to report detailed (de-identified) information on every mortgage loan application they receive. Data is sourced from financial institutions, where HMDA requires these institutions to report and publicly disclose mortgage information. This dataset includes the applicant's race, ethnicity, income, loan type, loan amounts, etc. HMDA data is the most comprehensive public source of information on mortgage lending in the United States. It is commonly used to track lending trends, identify potential discrimination, and develop fair lending policies (Cherian, 2014). The Consumer Financial Protection Bureau (CFPB) makes HMDA data available for free download on their website. Through the HMDA website, mortgage data is available per year and state in a .csv tabular format.

With the online portal, we obtained our data for the most recent year available in Massachusetts: 2022. We chose to include data from the most recent year of the HMDA dataset to test for the role of race and ethnicity in modern Massachusetts mortgage markets through data collected from different Massachusetts loan applicants (unit of observation). See Table 1 for a brief description of the dataset's variables and explanatory variables extracted from the dataset.

Dataset Variables

Table 1.
Dataset variables

Variable	Symbol	Definition
Occupancy Type	$principal_i$, $secondary_i$	The type of occupancy for which the mortgage application is for. Either principal residence, secondary residence, or investment (omitted). Extracted from property type feature.
Loan Amount	$loan_i$	The loan amount is applied for in dollars.
Applicant Race	$black_i$, $asian_i$, $native_i$, $pacific_i$	Dummy variable representing the applicant's race. The *white* race is omitted. Extracted from the primary applicant's race feature.
Applicant Ethnicity	$hispanic_i$	Dummy variable representing whether the primary applicant's ethnicity is Hispanic or not. Extracted from ethnicity feature.
Applicant Sex	sex_i	Dummy variable representing the primary applicant's sex (1 if male)

Applicant Income	$income_i$	Gross annual income of the primary applicant's household in thousands of dollars.
Application Outcome	Y_i	1: Loan processed. 2: Loan denied. Extracted from denial reason feature.

Based on economic theory, personal characteristics, risk of loan default (asset-risk/debt-to-income), and loan types are all determinants that play a role in mortgage lending policies (Ladd, 1998, 11; Cherian, 2014). In particular, the variables chosen from the 2022 Massachusetts HMDA dataset encompass these three categories: the applicant's income and loan amount affect the risk of default, while loan types and personal characteristics are given (Mardi et al., 2015).

Dataset Summary Statistics

Stata was used to calculate summary statistics. There are two types of variables in our data: continuous and discrete. We start with the continuous variables first. The two continuous variables in our dataset are the loan amount ($loan_i$) and the applicant income ($income_i$), so we calculate the mean, standard deviation, minimum, and maximum of those variables first. See Table 2 and Table 3 for the summary statistics of each variable.

Table 2.
Descriptive statistics of continuous variables.

Variable	Observations	Mean	Std Dev	Min	Max	IQR
Loan Amount	304,925	408.21	1208.515	5	203000	105000
Applicant Income	276,757	175.55	593.03	14	109947	112

Note. Loan Amount and Applicant Income are in thousands of dollars.

Table 3.
Percentile statistics of continuous variables.

Variable	Min	1%	25%	50%	75%	99%	Max

Loan Amount	5	25	155	305	485	1965	203000
Applicant Income	1	14	79	120	191	915	109947

We examine the dataset's discrete variables: property type, applicant race, applicant ethnicity, and applicant sex. See Table 3 for the frequency and observations per discrete variable.

Table 4.
Descriptive statistics of discrete variables.

Variable	Observations	Number of Groups	Group	Observations of Group	Percentage of Variable
Property Type	304,925	3	1 (Principal)	274,945	90.168%
			2 (Secondary)	8,179	2.683%
			3 (Invested)	21,801	7.149%
Applicant Race	227,297	5	1 (Native)	1,512	0.665%
			2 (Asian)	18,099	7.963%
			3 (Black)	18,564	8.167%
			4 (Pacific)	297	0.131%
			5 (White)	188,915	83.074%
Applicant Ethnicity	230,212	2	1 (Hispanic)	21,405	9.298%
			2 (Not Hispanic)	208,807	90.702%
Applicant Sex	254,477	2	1 (Male)	157,111	61.74%
			2 (Female)	97,366	38.26%
Outcome	296,579	2	1 (Approved)	271,282	91.470%
			2 (Denied)	25,297	8.530%

Analysis of Summary Statistics

As shown by Table 3, the maximum value of the loan amount variable is much higher than the 99% percentile, indicating that the maximum observation is an egregious outlier. Therefore, we removed this observation from the dataset. Furthermore, the loan amount variable mean of 408.21 is higher than the median of 305 (thousands of dollars), which shows that the loan amount variable is skewed right, indicating a concentration of values towards the lower end of the distributions and a few outliers pulling the mean to the right. However, Cherian (2014) did not decide to apply the natural log function to the loan amount number, and we decided to do the same. The same may be valid for applicant income, also shown in Tables 2 and 3. Because of the right-skewed distribution, theory suggests using the natural log of these values as dependent variables for our regression model.

As for the discrete variables, most of the observations come from a particular group: specifically, white males looking for a single-family house loan. There is limited variability in the data, which can affect the accuracy and generalization of our regression model. It may also represent bias in our regression analysis since the dataset may not represent the broader population seeking loans, so the regression estimates may not truly reflect the relationship between race, ethnicity, and loan outcomes in the Massachusetts mortgage market.

Model and Empirical Strategy

Cherian (2014) proposed the following model (Equation 1) for predicting loan application outcomes with logit regression that is linear in the variables.

Equation 1

$$L:\ P(Y_i) = \beta_0 + \beta_1 race_i + \beta_2 income_i + \beta_3 assetrisk_i + \beta_4 year_i + \beta_5 loan_i + \beta_6 property_i + \varepsilon_i$$

However, the 2022 dataset does not contain asset risk or property-type data points. As a result, we included the occupancy type variable instead. We did not find an adequate replacement variable for asset risk. However, loan amount and family income should be sufficient to describe the family's financial well-being. We further evaluate this decision in the discussion. So, we propose our binary logit regression model in Equation 2.

Equation 2

$$L: P(Y_i) = \beta_0 + \beta_1 income_i + \beta_2 loan_i + \beta_3 black_i + \beta_4 asian_i + \beta_5 native_i + \beta_6 pacific_i + \beta_7 ethnicity_i + \beta_8 principal_i + \beta_9 secondary_i + \beta_{10} sex_i + \varepsilon_i$$

Further description of the variables used in Equation 2 can be found in Table 1. Note that race, ethnicity, sex, and occupancy type variables are dummy variables.

Coefficient Hypothesis

The following table (Table 5) lists the construction of our hypothesis and the analysis of each coefficient in our specified model (Equation 2).

Table 5.
Hypothesis construction for each coefficient.

Coefficient	Hypothesis	Analysis
β_0	$H_0: \beta_0 = 0$ $H_A: \beta_0 \neq 0$	We constructed a two-sided hypothesis to test for significance, as there was no clear suggestion on what sign to expect.
β_1	$H_0: \beta_1 \leq 0$ $H_A: \beta_1 > 0$	Loan providers usually favor higher incomes as they are more likely to pay back mortgages (Consumer Financial Protection Bureau, 2023; Mardi et al., 2015).
β_2	$H_0: \beta_2 \leq 0$ $H_A: \beta_2 > 0$	The loan amount should hurt the loan application status. Higher loans would mean mortgage providers take on greater risks.
β_3	$H_0: \beta_3 \geq 0$ $H_A: \beta_3 < 0$	As we test for discrimination in house mortgage markets, we expect to see adverse effects of identifying as a minority race.
β_4	$H_0: \beta_4 \geq 0$ $H_A: \beta_4 < 0$	Same reasoning as above.
β_5	$H_0: \beta_5 \geq 0$ $H_A: \beta_5 < 0$	Same reasoning as above.
β_6	$H_0: \beta_6 \geq 0$ $H_A: \beta_6 < 0$	Same reasoning as above.
β_7	$H_0: \beta_7 \geq 0$ $H_A: \beta_7 < 0$	Same reasoning as above.
β_8	$H_0: \beta_8 \geq 0$ $H_A: \beta_8 < 0$	Cherian (2014) finds that principal occupancy in a home decreases the probability of loan application success.

β_9	$H_0: \beta_9 = 0$ $H_A: \beta_9 \neq 0$	We are unsure of any significance in the effect of secondary occupancy.
β_{10}	$H_0: \beta_{10} \leq 0$ $H_A: \beta_{10} > 0$	As we test for discrimination in house mortgage markets, we expect to see adverse effects of identifying as a female.

We intend to estimate this model with binomial logits; the results are discussed below.

Results

Several variables in our estimated model exhibit statistically significant relationships, as shown in Table 6 and Equation 3. Income, loan amount, race, ethnicity, and property type play significant roles. The model demonstrated a weak fit, evidenced by a log-likelihood of -74173, a likelihood ratio chi-square of 26503 with a probability close to 0, and a pseudo-R-squared of 0.1516.

Equation 3

$$L: \widehat{P(Y_i)} = \underset{(0.38)}{7.7} + \underset{(0.00014)}{0.012} income_i - \underset{(0.000033)}{2.7 \times 10^{-6}} loan_i - \underset{(0.020)}{0.92} black_i + \underset{(0.047)}{1.2} asian_i - \underset{(0.078)}{0.24} native_i$$

$$- \underset{(0.17)}{0.22} pacific_i - \underset{(0.020)}{0.77} ethnicity_i - \underset{(0.38)}{6.0} principal_i + \underset{(0.80)}{3.2} secondary_i + \underset{(0.016)}{0.21} sex_i$$

$$N = 296,579 \qquad \overline{R}^2 = 0.1516 \qquad \chi^2 = 26503$$

Table 6.

Statistics of binary logit model.

Variable	Coefficient	S. E.	Wald Statistic	p-value	0.95 Confidence Interval	
Income	0.012	0.0001389	86.85	0.000	0.0117893	0.0123337
Loan Amount	-2.68 x 10^{-6}	0.0000329	-81.41	0.000	-2.74 x 10^{-6}	-2.61 x 10^{-6}
Black	-0.916	0.0201849	-45.39	0.000	-0.9557054	-0.8765819
Asian	1.195	0.0469902	25.44	0.000	1.103146	1.287344
Native	-0.244	0.077757	-3.14	0.002	-0.3968229	-0.920212
Pacific	-0.222	0.1688081	-1.32	0.188	-0.5531539	0.1085617

Ethnicity	-0.770	0.0195467	-39.43	0.000	-0.8090227	-0.7324012
Principal	-6.011	0.3814799	-15.76	0.000	-6.758759	-5.263385
Secondary	3.226	0.7962662	4.05	0.000	1.665708	4.787014
Sex	0.213	0.0145273	14.67	0.000	0.1846791	0.2416252
Constant	7.731	0.3815379	20.26	0.000	6.983167	8.478768

For our analysis, we used the Wald test to assess whether the variables have statistically significant effects on mortgage application outcomes. For instance, if the test statistic for a particular coefficient exceeds the critical value or the p-value is less than 0.05, we can conclude that the corresponding variable is statistically significant at the 0.05 significance level. Among the estimated coefficients, income, and loan amount significantly affected mortgage application outcomes ($p < 0.05$). Furthermore, race and ethnicity variables showed some notable impacts, with Black applicants facing an expected negative impact of -28.5% compared to White applicants ($\widehat{\beta_3} = -.916,\ p < 0.05$) ceteris paribus and Asian applicants experiencing a positive impact of 29.9% compared to White applicants ($\widehat{\beta_4} = 1.195$), which is not significant and goes against our hypothesis. The coefficient for the Native race also showed a negative effect ($\widehat{\beta_5} = -.2444,\ p < 0.05$), while the coefficient ($\widehat{\beta_5}$) for the Pacific race did not reach statistical significance ($p > 0.05$). Additionally, as a dummy variable, Hispanic ethnicity yielded a significant coefficient of $\widehat{\beta_7} = -.770$ ($p < 0.05$).

Regarding the property type, being a principal home was associated with a considerable negative coefficient ($\widehat{\beta_8} = 6.011$), while being a secondary home showed a positive coefficient ($\widehat{\beta_9} = 3.2263$), both statistically significant ($p < 0.05$) when compared to an invested home.

Furthermore, $\widehat{\beta_{10}} = .213$ it signifies that a male is, on average, 5% more likely to be accepted for a mortgage loan than a female ceteris paribus.

Discussion

We also decided to conduct linear regression where, instead, income or loan amount was the dependent variable of a standard linear model. See equations 4 and 5 for their specifications.

Equation 4

$$L: P(Y_i) = \beta_0 + \beta_1 loan_i + \beta_2 black_i + \beta_3 asian_i + \beta_4 native_i + \beta_5 pacific_i + \beta_6 ethnicity_i + \beta_7 principal_i + \beta_8 secondary_i + \beta_9 sex_i + \varepsilon_i$$

Equation 5

$$loan_i = \beta_0 + \beta_1 income_i + \beta_2 black_i + \beta_3 asian_i + \beta_4 native_i + \beta_5 pacific_i + \beta_6 ethnicity_i + \beta_7 principal_i + \beta_8 secondary_i + \beta_9 sex_i + \varepsilon_i$$

Although we hoped these models would provide more insight into the correlation between loan applicant characteristics and the applicant's income and loan amount, they showed poor fit ($\overline{R^2} = 0.073,\ 0.096$ respectively for equations 4 and 5) yet achieved global significance. Furthermore, we suspected multicollinearity because one variable (β_5) had insignificant coefficients in both specifications, yet we found an absence of collinearity in our variables ($\overline{VIF} = 1.12$) for Equation 5. These regression results can be found in Appendix 1.

We also performed an alternate specification with a debt-income ratio variable as an alternative to the asset-risk variable proposed by Cherian (2014), measuring the applicant's riskiness to mortgage default (Mardi et al., 2015). Furthermore, we specified slope-dummy variables denoting the marginal impacts of race and ethnicity on income/loan amount's effect on loan application outcome. See equations 6 and 7 for their specifications.

Equation 6

$$L: P(Y_i) = \beta_0 + \beta_1 income_i + \beta_2 loan_i + \beta_3 black_i income_i + \beta_4 asian_i income_i + \beta_5 native_i income_i + \beta_6 pacific_i income_i + \beta_7 ethnicity_i income_i + \beta_8 principal_i + \beta_9 secondary_i + \beta_{10} sex_i$$

$$+ \beta_{11} debt\_income\_ratio_i + \varepsilon_i$$

Equation 7

$$L: P(Y_i) = \beta_0 + \beta_1 income_i + \beta_2 loan_i + \beta_3 black_i loan_i + \beta_4 asian_i loan_i + \beta_5 native_i loan_i + \beta_6 pacific_i loan_i + \beta_7 ethnicity_i loan_i + \beta_8 principal_i + \beta_9 secondary_i + \beta_{10} sex_i + \beta_{11} debt\_income\_ratio_i + \varepsilon_i$$

However, we received similar results, with a poor fit ($\overline{R^2} = 0.1678, 0.1675$), but the coefficients still had global significance. These additional regression results can also be found in Appendix 2.

Conclusion

Our analysis of mortgage market outcomes underscores the nature of factors that influence lending decisions. These findings highlight the significance of socioeconomic and demographic variables in shaping mortgage application outcomes in Massachusetts. Income, loan amount, race, ethnicity, property characteristics, and gender emerged as determinants.

Our examination showed that income and loan amount significantly influenced mortgage application outcomes, reflecting the importance of financial stability and borrowing capacity on the outcome of giving a loan from a bank or credit union. Moreover, race and ethnicity variables also played a crucial role, with Black and Asian applicants experiencing contrasting effects on mortgage acceptance probabilities. Ethnicity as a categorical variable also demonstrated a notable impact, emphasizing the importance of considering broader sociocultural factors in lending practices. By identifying the critical determinants of mortgage approval, our findings offer valuable insights for policymakers, lenders, and stakeholders seeking to promote fairness and transparency in mortgage lending practices.

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Appendix

Appendix 1.

```
. regress income loan_amount black asian native pacific hispanic_ethnicity principal_property secondary_property sex_female
```

Source	SS	df	MS
Model	7.1468e+09	9	794085153
Residual	9.0185e+10	276,747	325876.888
Total	9.7332e+10	276,756	351689.638

Number of obs	=	276,757
F(9, 276747)	=	2436.76
Prob > F	=	0.0000
R-squared	=	0.0734
Adj R-squared	=	0.0734
Root MSE	=	570.86

income	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
loan_amount	.4118329	.0030369	135.61	0.000	.4058806	.4177852
black	-33.60648	4.406579	-7.63	0.000	-42.24326	-24.96971
asian	-43.82717	4.502738	-9.73	0.000	-52.65241	-35.00192
native	14.85531	14.88365	1.00	0.318	-14.31623	44.02685
pacific	-19.24008	33.81241	-0.57	0.569	-85.51148	47.03132
hispanic_ethnicity	-38.04136	4.137293	-9.19	0.000	-46.15034	-29.93238
principal_property	-53.91433	5.006363	-10.77	0.000	-63.72667	-44.102
secondary_property	161.4778	8.193206	19.71	0.000	145.4194	177.5363
sex_female	-14.38891	2.298377	-6.26	0.000	-18.89367	-9.884158
_cons	84.7607	5.110569	16.59	0.000	74.74412	94.77727

```
. regress loan_amount income black asian native pacific hispanic_ethnicity principal_property secondary_property sex_female
```

Source	SS	df	MS
Model	3.5247e+09	9	391627876
Residual	3.3132e+10	276,747	119718.025
Total	3.6656e+10	276,756	132449.722

Number of obs	=	276,757
F(9, 276747)	=	3271.25
Prob > F	=	0.0000
R-squared	=	0.0962
Adj R-squared	=	0.0961
Root MSE	=	346

loan_amount	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
income	.1512958	.0011157	135.61	0.000	.1491091	.1534826
black	-5.576171	2.671141	-2.09	0.037	-10.81153	-.3408094
asian	127.3503	2.718876	46.84	0.000	122.0214	132.6792
native	-56.30947	9.02054	-6.24	0.000	-73.98949	-38.62946
pacific	-34.15459	20.49402	-1.67	0.096	-74.32231	6.013134
hispanic_ethnicity	-10.73548	2.507963	-4.28	0.000	-15.65102	-5.819941
principal_property	-22.36197	3.034755	-7.37	0.000	-28.31001	-16.41394
secondary_property	242.8658	4.947995	49.08	0.000	233.1679	252.5638
sex_female	-55.13289	1.389225	-39.69	0.000	-57.85573	-52.41005
_cons	361.1014	3.022144	119.49	0.000	355.1781	367.0247

Appendix 2.

Logistic regression

Number of obs = 199,418
LR chi2(10) = 20645.33
Prob > chi2 = 0.0000
Pseudo R2 = 0.1678

Log likelihood = -51181.748

outcome	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
income	.0134819	.0001926	70.01	0.000	.0131045	.0138593
loan_amount	-.0031175	.0000419	-74.35	0.000	-.0031997	-.0030353
black_income	-.0084757	.0001963	-43.19	0.000	-.0088604	-.008091
asian_income	.0077482	.0004338	17.86	0.000	.0068979	.0085985
native_income	-.0038995	.000793	-4.92	0.000	-.0054538	-.0023452
pacific_income	-.0014401	.0019227	-0.75	0.454	-.0052086	.0023284
ethnicity_income	-.0071169	.0001914	-37.19	0.000	-.007492	-.0067419
principal_property	-9.460242	1.026347	-9.22	0.000	-11.47184	-7.44864
secondary_property	0	(omitted)				
sex_female	.2169897	.0173478	12.51	0.000	.1829886	.2509907
debt_to_income_numeric	-.0281503	.0007571	-37.18	0.000	-.0296342	-.0266663
_cons	12.4621	1.024138	12.17	0.000	10.45483	14.46938

Note: 0 failures and 1123 successes completely determined.

Logistic regression

Number of obs = 199,418
LR chi2(10) = 20600.55
Prob > chi2 = 0.0000
Pseudo R2 = 0.1675

Log likelihood = -51204.138

outcome	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
income	.0124606	.0001902	65.53	0.000	.0120879	.0128334
loan_amount	-.0028585	.0000427	-66.88	0.000	-.0029423	-.0027747
black_loan_amount	-.0026415	.0000568	-46.47	0.000	-.0027529	-.0025301
asian_loan_amount	.002252	.0001087	20.71	0.000	.0020388	.0024651
native_loan_amount	-.0014879	.0002327	-6.39	0.000	-.001944	-.0010318
pacific_loan_amount	-.0012041	.0005195	-2.32	0.020	-.0022222	-.000186
ethnicity_loan_amount	-5.82e-06	2.85e-07	-20.43	0.000	-6.38e-06	-5.26e-06
principal_property	-8.810618	1.03017	-8.55	0.000	-10.82971	-6.791522
secondary_property	0	(omitted)				
sex_female	.230232	.0174437	13.20	0.000	.196043	.2644209
debt_to_income_numeric	-.0286103	.0007567	-37.81	0.000	-.0300934	-.0271271
_cons	11.79137	1.028635	11.46	0.000	9.775279	13.80745

Note: 0 failures and 791 successes completely determined.