Master in Econometrics and Statistics

Applied Econometrics

March 2024

Are credit allocation models discriminatory? The American experiment

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Abstract

In this paper, we aim to assess the fairness of American credit allocation models used by financial institutions to evaluate a loan application. Our data gathers a comprehensive sample of loan applications for each state of the United States, in 2022, taken from the Consumer Financial Protection Bureau. We use a logistic model to analyze the probability of credit denial among individuals according to their sex and their race, and controlling for financial variables and the age. We first focus on Michigan and we then extend our study to all the other states of the United States. Our study demonstrates that credit allocation models are discriminating. We do not show great evidence of gender discrimination but we reveal a racial discrimination in the sense where Asians, Afro-Americans, and Natives are more likely to get their application rejected. Namely, on average in the United States in 2022, being Black increases the probability of being denied a loan by 10 percentage points, compared to being White.

1 Introduction

Many people on Earth aspire to become homeowners. However, in order to achieve this goal, it is often necessary to obtain a loan. To apply for a loan, you must submit an application. The bank will then evaluate your application and determine if you are eligible. To make this decision, they use a classification model that aims to discriminate between good-type borrowers and bad-type borrowers.

Ethical questions arise when those models include discriminatory variables that are *a priori* not related at all to a loan reimbursement capability, compared to purely financial variables. The objective of this paper is to determine if these variables affect credit allocation. If they do, we aim to estimate theses effects and measure the difference in rejection rates between the discriminated groups and others. Therefore, we would like to answer the following question: **Are credit allocation models discriminatory?**

In credit markets, the main objective of a bank is to be able to distinguish between customers who will repay the loan and those who will not. Since the bank's purpose is to make a profit, it wishes not to lose money by lending to customers who will not be able to pay back their debt. Following this idea, Hurlin et al. (2021) studied the fairness of credit scoring models. In their study, they assess the presence of statistically significant differences in rejection rates or interest rates, denoted as indicators of fairness disparity, across protected attributes such as gender, age, or racial origin. Their results show the unfairness of the models and non-legitimate discrimination, showing statistically significant results of discrimination of women and minorities.

As highlighted by Cozarenco and Szafarz (2014), disparities persist in credit access along gender lines. Their examination of micro-finance institutions in France highlights not only the relative scarcity of access to credit for women but also the consistent pattern of lower credit amounts granted to them. Similarly, investigating gender dynamics in small-business lending using comprehensive data from a Brazilian microfinance institution, Agier and Szafarz (2011) unveil evidence of gender bias. Their findings highlight a discernible discrimination against women entrepreneurs, manifested in lower loan disbursements and reduced loan approval frequency.

Empirical studies aiming to identify the determinants of access to credit mostly present results on classic factors. Based on this, Mwangi (2009) make an empirical analysis based on data that contains information on 4420 households in Kenya. Following his study, he established that demographic and socioeconomic characteristics influence one's access to credit. Furthermore, according to him, age, gender or education have an impact on the access to credit.

In their study, Bayer et al. (2017) give a more specific point of view, focusing on examining racial and ethnic differences in high-cost mortgage lending in seven diverse metropolitan areas from 2004 to 2007. In their results, they identified large racial and ethnic differences in the likelihood of receiving a rate spread mortgage in the home purchase market after controlling for detailed borrower and that Hispanic and Black individuals are disproportionately more prone to secure high-cost mortgages when seeking loans. Also examining racial disparities in housing finance, Myers et al. (1995) provide a compelling analysis based on the Home Mortgage Disclosure Act data for New Jersey in 1990. Their study reveals a pronounced inequality in loan approvals, with black applicants being more than twice as likely to face denial compared to white applicants. They concluded that an alarming 70 percent of the disparity in loan denials between black and white applicants could not be accounted for by differences in borrower characteristics, loan specifics, neighborhood factors, or credit quality.

More recently, Agarwal et al. (2023) studied racial discrimination in lending using 157.269 loan applications during 2017 in New York. The study highlights the persistent issue of racial discrimination in lending decisions and posits that advanced AI models, particularly those utilizing Shapley-type explainable AI techniques, can bring transparency and accountability to these decisions. By using a Random Forest algorithm as an example, it demonstrates that machine learning models can be evaluated not only on predictive accuracy but also on ethical grounds. This suggests a path forward where AI could help reduce racial bias in lending, supporting a more equitable financial system.

Finally, in the case where two applicants apply for a mortgage as a couple, Hagendorf et al. (2022) study the consequences of the legalization of same-sex marriages across the United States. They expose a denial gap between same sex-borrowers and different-sex borrowers, which is not reduced when the company relies less on human loan officers. Thereby, it appears even more pertinent to question the morality of credit allocation models.

2 Econometric modeling

2.1 General specification and assumptions

In this section, we justify our econometric approach by the nature of our target variable *deny* and the assumptions that we have to make to obtain a model with desirable properties.

We aim to explain if the gender or the race of the applicant influence their credit denial or not. Since the variable *deny* takes the value 1 if the loan is rejected by the bank and 0 otherwise, we can write it as follows:

$$deny_i = \mathbf{1}_{\{U_i \leq 0\}}$$

where U_i is the utility function of the bank associated to the loan for individual i (if it is negative, the bank denies the loan and $deny_i = 1$).

We then assume:

- (H1) The utility function of the bank U_i depends on financial variables but also on some socio-demographical characteristics, including our discriminatory variables. It also includes an error term ε_i.
- (H2) The utility function of the bank U_i is parametric (a constant and K parameters for K explanatory variables).
- (H3) ε_i follows a logistic distribution.

We can thus write $U_i = X_i'\beta + \varepsilon_i$ where $X_i'\beta$ is a vector of the explanatory variables that we will select (and $\beta \in \Theta \subset \mathbb{R}^{K+1}$).

At this stage, a logistic regression model seems the most natural to explain the probability of a loan to be rejected or not. Our main econometric specification will be the following logistic model:

$$(\mathcal{M}) \quad : \quad \mathbb{P}(y_i = 1) = \frac{1}{1 + e^{X_i'\beta}}$$

We now want to choose relevant variables to represent the utility function of the bank $U_i = X_i'\beta + \varepsilon_i$ and we will then estimate the model that we obtain by the Maximum Likelihood (ML) method, knowing the likelihood function $f(\beta, y_i|X_i;)$ from the fact that $y_i|X_i \sim \mathcal{B}\left(\frac{1}{1+e^{X_i'\beta}}\right)$.

This method is valid and yields consistent, asymptotically efficient and normally distributed estimates under some extra assumptions (H4)-(H9), detailed in 5.

We will not verify some of these assumptions which are more mathematically-convenient. However, we can claim that assumption (H7) is credible in our context as our data is cross-sectional. Besides, to verify (H9) namely the non-singularity of the information matrix, we propose to check multicolinearity among our variables.

Check for multicollinearity

To justify (H9) annd measure our model's multicollinearity we will use GVIF (Generalized Variance Inflation Factor). The GVIF is an extension of the Variance Inflation Factor (VIF), which measures the inflation in the variance of the estimated regression coefficients due to multicollinearity. While VIF is typically used for linear regression models, GVIF extends this concept to generalized linear models and namely, serves our purpose for the logistic model we wish to estimate.

The GVIF for a particular predictor variable X_i is calculated by fitting a separate model where X_i is regressed on all other predictor variables X_j, excluding itself:

$$GVIF_i = \frac{1}{1 - R_i^2}$$

Where R_i^2 is the R^2 value obtained from regressing X_i on all the other predictor variables.

The GVIF represents how much the variance of the estimated regression coefficient for X_i is inflated due to multicollinearity. If its value is close to 1, it indicates that there is little multicollinearity associated with that particular predictor variable. However, if the GVIF is significantly greater than 5 (commonly a threshold of 5 or 10 is used), it suggests that multicollinearity may be present, and the interpretation of the coefficient estimates associated with that variable should be approached with caution.

Table 6 shows that the maximum value of GVIF is 2.41 for the logarithm of the loan amount variable. This means we have a moderate multicolllinearity and can interpret the results of our models appropriately.

2.2 Model

Naively, since we want to evaluate the impact of our discriminatory variables on the probability of having its application denied, we choose :

$$U_i = \beta_0 + \beta_1 sex_i + \beta_2 race_i + \varepsilon_i$$

and plugging it in $(\mathcal{M})$, we denote the obtained model $(\mathcal{M}1)$.

It is obvious that there are confounders and endogeneity in the model $(\mathcal{M}1)$. Indeed, we have to compare populations with similar characteristics, whereas until here, we suspect other variables to be correlated with the discriminatory variables and the probability of having its credit denied (*omitted* variables, contained in the error term). Therefore, we need to add some control variables.

Myers and Samuel (1995) include naturally the household income (*income*), but also the amount of the loan (*loan_amount*) and if the loan was a home purchase or a home improvement (included in *loan_purpose*). They also suggest controlling for the number of people aged 65 or older, and 18 or younger in the household, while Mwangi (2011) includes the age of the applicant (*age*). Data about the household being incomplete, we will follow the latter. Moreover, we consider the duration of the loan (*loan_term*) as an important factor of the probability of being denied (Hurlin et al., 2021). Finally, we account for the "size of the project" suggested by Cozarenco and Szafarz (2014) when they study business applications loans, and that may correspond in our case to the *property_value*.

Altogether, the literature analysis leads us to add the following variables : *age*, *loan_term* and *loan_purpose*, as well as *amount*, *income*, *property_value* that we transform with the logarithm function. Indeed, we assume a concave relation between the income and the probability of being denied. Moreover, we believe that there is an income threshold from which all applications are accepted, irrespective of an applicant's sex or ethnicity. This effect is well captured by taking the logarithm of the income-related variables which thus gives less weight to high incomes for instance.

Hence, we derive the following model:

$$U_i = \beta_0 + \beta_1 \mathrm{sex}_i + \sum_{k=2}^{4} \beta_k \cdot \mathrm{race}_i^{(k)} + \sum_{k=5}^{11} \beta_k \cdot \mathrm{age}_i^{(k)} + \sum_{k=12}^{15} \beta_k \cdot \mathrm{loan\_purpose}_i^{(k)}$$

$$+ \beta_{16} \log(\mathrm{amount}_i) + \beta_{17} \log(\mathrm{income}_i) + \beta_{18} \log(\mathrm{property\_value}_i) + \beta_{19} \mathrm{loan\_term}_i + \varepsilon_i$$

and plugging it in $(\mathcal{M})$, we denote the obtained the following model $(\mathcal{M}2)$:

$$(\mathcal{M}2): \quad \mathbb{P}(y_i = 1) = \frac{1}{1 + e^{U_i - \varepsilon_i}} \tag{1}$$

Note that the reference level for the categorical variable *sex* is "Men", the reference for *race* is "White", the reference for *age* is "35-44", and the reference for *loan_purpose* is "Home purchase", which represent the most frequent categories for each variable.

3 Data

Our aim is to answer the question for the United States as a whole, but to begin, we will detail the analysis for one state in particular, an analysis that can be extended to all states.

3.1 Source

Each year, in every state of the USA, under the *Home Mortgage Disclosure Act (HMDA)*, banks have to report loan applications they have received along with some characteristics of the applicants (sex, income, purpose of the loan, etc.). It is reported to the Consumer Financial Protection Bureau [see 1].

In this study, we use the most recent data we have at our disposal, that is 2022, and we first perform an analysis on the state of Michigan before comparing our results to other states, using a similar data.

3.2 Initial dataset

Our initial dataset is a cross-sectional and individual-leveled data (each row corresponds to one application). It contains 470,377 observations described by 99 variables. The variables contains information on the loan (decision, amount, etc.), the applicant (age, sex, ethnicity, income, etc.) and the financial institution(Description of variables). It is comprehensive, as it corresponds to all loan applications processed in Michigan in 2022. Thereby, **the initial dataset can be seen as the population**. However, we do not need all 99 variables to answer our questions, and some variables have numerous missing values. We therefore need to clean the data in order to work with a complete and usable dataset.

3.3 Data manipulation

We hereby present the details of our choices. Firstly, our target variable *deny* did not exist as such, so we had to create it. To do this, we used the variable *action_taken* which takes 8 possible values, one of which is "loan originated". The *deny* variable therefore equals 0 if action taken is loan originated, 1 otherwise.

For the *race* variable, some modalities represented less than 0.5% of the dataset. We decided to remove them. Finally, we grouped the "Alaska Native" and "Native Hawaiian" modalities into a single "Native" category.

To deal with missing values, we proceeded as follows. For each variable stated in ($\mathcal{M}2$), there may have been a few missing values. We decided to delete all rows where a variable had a missing value. Given the size of our dataset, we did not see any drawbacks to this method. However, we will be checking the representativeness of our final sample with the initial data later on.

As the aim of our study is to demonstrate discrimination in the credit market, we decided to remove extremely wealthy people from our sample. We therefore consider only loan amounts and property values below $1 million and incomes below $500,000. [see (Table 1)]

3.4 Final sample and representativeness

Our final dataset has 243.334 observations and contains the 10 following variables : our target variable -*deny* (a binary variable equal to 1 if the application was denied, 0 otherwise)-, some socio-demographic variables *sex*, *age*, *race* and some financial variables *loan_amount*, *income*, *property_value*, *loan_term* and *loan_purpose*.

Our dataset contains 201,219 successful applications (83 %) and 42,115 denied ones. The majority of the applicants are men (63% against 37% for women) [see Table 3]. In our data we have 87% of White, 8.8% of Black, 3.5% of Asian and 0.7% of Native [see Table 2]. We give other descriptive statistics in the appendix [see Tables 3, 4 5] and Figures 2, 3,4, 5, 6, 7, 8, 9, 10]. We also notice that income is distributed differently depending on race. Indeed, it is significantly lower for black people and Natives, as can be seen in 11].

To verify that our final sample is representative, knowing that our *initial* dataset is seen as the population, the method is to compare the distribution between the initial dataset and our final one, for some interest variables. For the qualitative variables (*sex*, *race*, *age*), we verify that the proportions between the population and the final sample are the same at more or less 1% (for each category). For the quantitative variables (*loan_amount*, *income*, *property_value*), we verify that the median between the population and the final sample is the same at more or less 1 unit.

For example, for the quantitative variable *income*, we compare $Me(income) = \$75,000$ and $Me(sample) = \$76,000$. For the qualitative variable *race*, we observe 9% of black people in the population and 8.8% in our sample.

This short analysis allows to conclude that our final sample is representative of the population of loan applications in Michigan, in 2022.

4 Results

To further evaluate the predictive capabilities (accuracy) of our model, we will randomly split our data into a training set and a test set (80% and 20%, respectively). We estimate $\mathcal{M}2$ on the train set by the MLE method and report the results in table 7.

Firstly we note that, almost all coefficients are significant at 1%. The signs of the coefficients associated to the modalities of the variable *race* are positive as we could expect from the literature, meaning that in this model, an Asian, Black or Native person is more likely to get their credit denied than a White one. The variable *sex* is also significant. Contrary to what we could expect from the literature, the coefficient associated to sex is negative (men being the reference). This means that being a woman reduces the probability of deny.

Concerning the control variables, for the financial ones we note that the richer the individual, the lower their probability of deny and the higher the amount of the loan, the greater the probability of deny. For any loan purpose that differs from Home Purchase (the reference value), the probability of refusal increases.

Magnitude of coefficients in a logistic model cannot be interpreted directly. Thus, we decided to analyze the average marginal effects (AME) [see Table 8]. For a given variable, the AME represents the average change in the probability of being denied due to a one-unit change in the given variable, holding all other variables constant.

For the variable *Black*, the AME is 0.1168. This means that, on average, being Black increases the probability of being denied a loan by **11.68 percentage points**, compared to White individuals, controlling for all other variables in the model. For Asian people and Natives, the probability of deny increases by respectively **6.9 and 6.8 percentage points** compared to being White. For the variable $Woman$, the AME is -0.011. This indicates that, on average, being a woman decreases the probability of being denied a loan by approximately **1.10 percentage points**, compared to being a man, while holding all other variables constant. The p-value associated with these effects are essentially zero, indicating that the effects are statistically significant.

In other words, according to this model, being Black, Asian or Native significantly increases the probability of loan denial compared to White individuals. Being a woman slightly decreases this probability, while controlling for factors such as age, income, loan amount, loan purpose, loan term and property value.

The confusion matrix [see Table 9] provides a detailed snapshot of the performance of our predictive model. With an overall accuracy of 83.3%, we observe that the model effectively classifies the majority of instances correctly. However, it misclassifies 7712 instances where loans are approved but predicted as denied, and 470 instances where loans are denied but predicted as approved. Nevertheless, our aim here is not to create a predictive model, but to understand and estimate the effect of each variable on the probability of deny. This is why we use the Average Marginal Effects as interpretation of our model.

Extension of the model to the 50 States of the USA

In order to extend our model to the other states of the US, we estimate the same model ($\mathcal{M}2$) using data from all the other states, in 2022.

This data has the same characteristics than the one from Michigan. First, the source is the same as it is taken from the Consumer Financial Protection Bureau, as well as their collection method (mandatory report of the financial institutions under HMDA). The data thus stays comprehensive for all the applications in a given state. Besides, the data has the same form in the sense where it contains the same variables. The cleaning process can thus be performed with the same code.

Definition. (Racial discrimination criterion) *We measure the racial discrimination (towards Afro-American people) of a state s with the AME of the variable Black for each state s.*

In a given state, the AME of the variable *Black* being strictly greater than 0 would imply that on average, Black people have a greater probability of being denied than a White person, while keeping the other variables constant.

Then, we visualize these AME in a map of the United States [see 14] where the color (from white to red) indicates the level of racial discrimination according to our criterion.

According to this criterion, the less racist state is Wyoming with an AME of the variable *Black* of 0.03 and the more racist one is Minnesota with an AME of the variable *Black* of 0.14. Furthermore, nationwide, the mean of the AME of the variable *Black* is 0.10.

Conclusion

In our first analysis of the state of Michigan, in 2022, we revealed significant racial discrimination. There, a black or an Asian person is more likely to get their credit application rejected. Indeed, being Black increases the probability of being deny by 11.7 percentage points, compared to being White. However, we did not show great evidence of gender discrimination. By contrast with the literature, we showed that being a woman reduces the probability of deny by 1.10 percentage point.

Then, extending our analysis using the same methodology, we showed that credit allocation models are discriminating in the whole United States, in 2022. Comparing the Average Marginal Effect of being Black for each state, we point out that, **on average in the United States of America in 2022, being Black increases the likelihood of being denied a loan by 10 percentage points, compared to being White**. It is important to notice that every state discriminates because every AME associated to variable *Black* is positive.

However, our analysis could still be extended. Firstly, one could consider European countries which share a similar culture (United Kingdom, France, etc.) and verifies if the racial bias is less frequent or less marked. One could also consider past years and compare if the situation has evolved positively (less racial discrimination). Finally, one could reproduce this study in future years, when the data is made available by the Consumer Financial Protection Bureau, and verify if the racial bias has persisted.

5 Appendix

Figure 1: Logo of the Consumer Financial Protection Bureau, source of our data

Data Appendix

Variable	Label	Type	Modality
derived_race	Race of the applicant	Categorical	White, Black, Asian and Native
loan_purpose	Purpose of the loan	Categorical	1 for Home purchase 2 for Home improvement 31 for Refinancing 32 for cash-out Refinancing 4 for Other Purpose
loan_amount	Amount of the loan	Numerical	between $1 and $1 million
loan_term	number of months after which the legal loan or application obligation will mature	Numerical	
property_value	value of the property in dollars	Numerical	between $1 and $1 million
income	Income of the applicant in dollars	Numerical	between $1 and $500,000
applicant_sex	Sex of the applicant	Categorical	1 for Male 2 for Female
applicant_age	Age of the applicant	Categorical	<25 25-34 35-44 45-54 55-64 65-74 >74
deny	Has the application been denied?	Dummy	

Table 1: Specifications of the variables included in our final dataset

Univariate descriptive statistics

Race	White	Black	Asian	Native
Proportions (%)	87.0	8.8	3.5	0.7

Table 2: Distribution of *race*

Sex	Men	Women
Proportions (%)	62.85	37.15

Table 3: Distribution of *applicant_sex*

Purpose	Home purchase	Home improvement	Refinancing	Cashout refinancing	Other
Proportions (%)	42	14	13	20	11

Table 4: Distribution of *loan_purpose*

Statistic	Mean	St. Dev.	Min	Max
loan_amount ($)	168,676.70	123,922.20	5,000	995,000
loan_term (in months)	313.23	85.44	1	480
property_value ($)	287,208.70	160,654.70	5,000	995,000
income ($*10^3$ $)	93.41	63.99	1	499

Table 5: Summary statistics for the quantitative variables

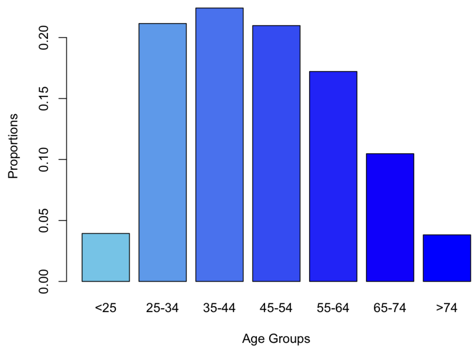

Figure 2: Distribution of *age*

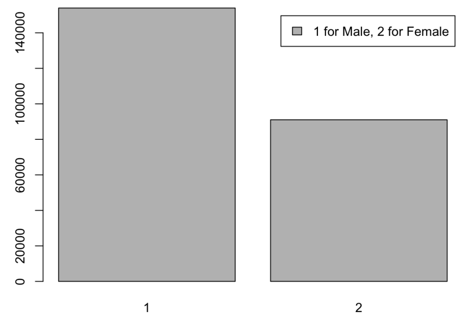

Figure 3: Distribution of the applicants' sex

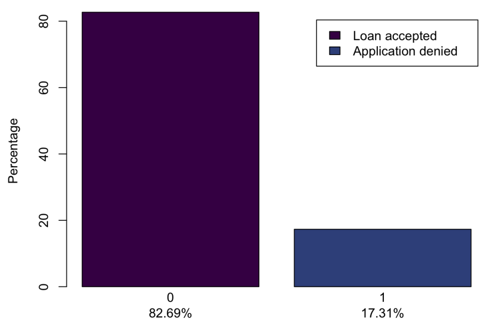

Figure 4: Distribution of *deny*

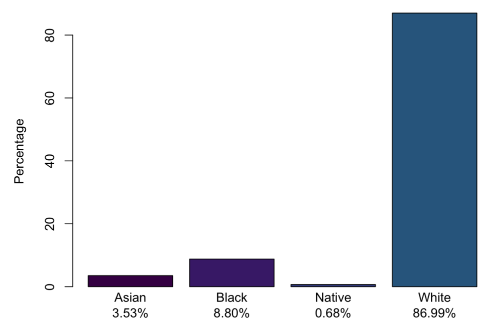

Figure 5: Distribution of *race*

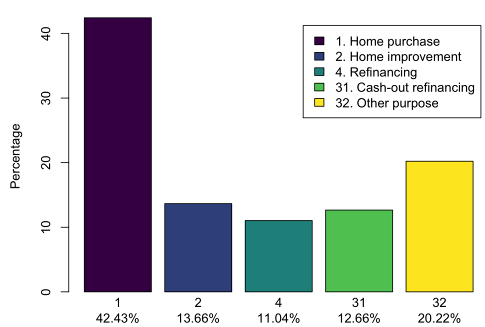

Figure 6: Distribution of *loan_purpose*

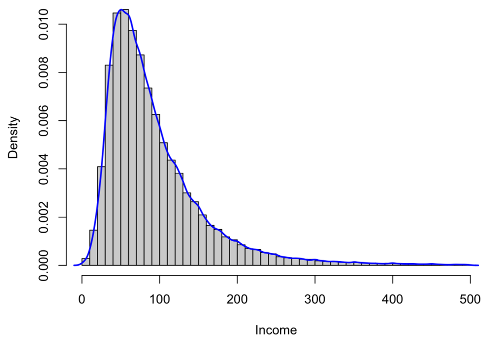

Figure 7: Histogram of *income*

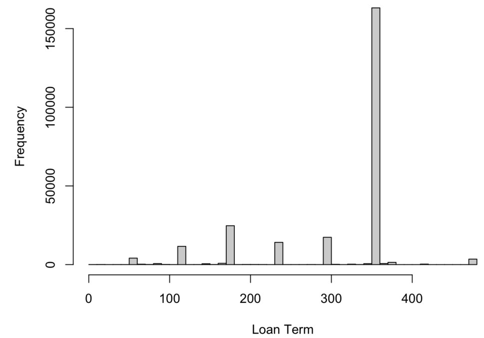

Figure 8: Histogram of *loan_term*

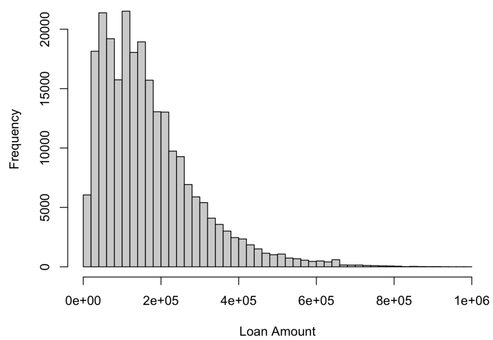

Figure 9: Histogram of *loan_amount*

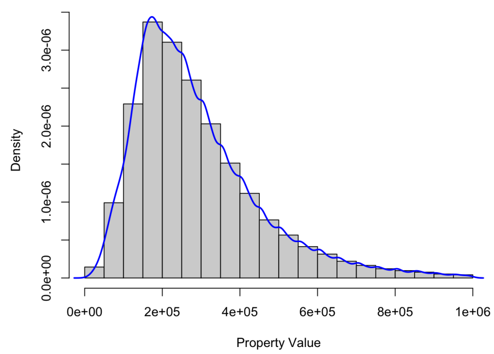

Figure 10: Histogram of *property_value*

Bivariate descriptive statistics

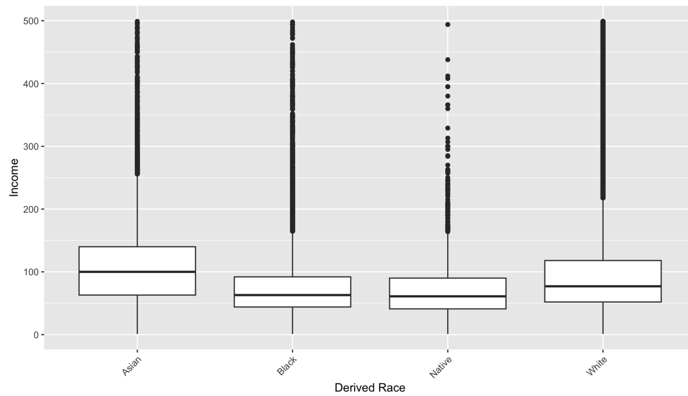

Figure 11: Distribution of the income by race

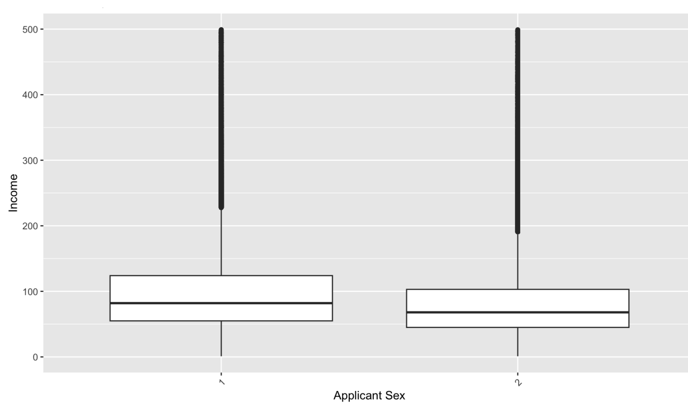

Figure 12: Distribution of the income by sex

Results of the VIF

Variable	**GVIF**	**Df**	**GVIF$^{\frac{1}{2Df}}$**
derived_race	1.093874	3	1.015067
loan_purpose	2.261727	4	1.107401
log_loan_amount	2.412945	1	1.553366
loan_term	1.190735	1	1.091208
log_property_value	1.972906	1	1.404602
log_income	1.490657	1	1.220925
applicant_sex	1.042179	1	1.020872
applicant_age	1.314415	6	1.023044

Table 6: Variance Inflation Factor (VIF) Values

Results of the model ($\mathcal{M}2$)

	Coefficient	(Std. Error)
(Intercept)	8.11^{***}	$(1.63e-01)$
Asian	0.50^{***}	$(3.51e-02)$
Black	0.78^{***}	$(1.95e-02)$
Native	0.49^{***}	$(6.56e-02)$
Age<25	-0.18^{***}	$(3.99e-02)$
Age>74	-0.23^{***}	$(3.26e-02)$
Age between 25-34	-0.15^{***}	$(2.08e-02)$
Age between 45-54	-0.0027	$(1.90e-02)$
Age between 55-64	-0.17^{***}	$(2.02e-02)$
Age between 65-74	-0.30^{***}	$(2.33e-02)$
log(income)	-0.70^{***}	$(1.26e-02)$
log(loan_amount)	0.048^{***}	$(1.22e-02)$
Home improvement	1.76^{***}	$(2.49e-02)$
Other purpose	1.91^{***}	$(2.53e-02)$
Refinancing	1.11^{***}	$(2.30e-02)$
Cash-Out Refinancing	1.11^{***}	$(1.95e-02)$
Loan term	0.0023^{***}	$(7.97e-05)$
log(property_value)	-0.33^{***}	$(1.60e-02)$
Woman	-0.087^{***}	$(1.33e-02)$
Observations	195,995	
Akaike Inf. Crit. (AIC)	160,542	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Estimated coefficients of ($\mathcal{M}2$)

Average Marginals Effects

	factor	AME	SE	z	p	lower	upper
1	Age<25	-2.32×10^{-2}	5.00×10^{-3}	-4.67×10^{1}	0.00	-3.29×10^{-2}	-1.34×10^{-2}
2	Age>74	-2.93×10^{-2}	4.00×10^{-3}	-7.39×10^{1}	0.00	-3.71×10^{-2}	-2.15×10^{-2}
3	Age 25-34	-2.00×10^{-2}	2.70×10^{-3}	-7.45×10^{1}	0.00	-2.52×10^{-2}	-1.47×10^{-2}
4	Age 45-54	-4.00×10^{-4}	2.60×10^{-3}	-1.44	8.85×10^{-1}	-5.40×10^{-3}	4.60×10^{-3}
5	Age 55-64	-2.24×10^{-2}	2.60×10^{-3}	-8.64×10^{1}	0.00	-2.74×10^{-2}	-1.73×10^{-2}
6	Age 65-74	-3.72×10^{-2}	2.80×10^{-3}	-1.33×10^{2}	0.00	-4.27×10^{-2}	-3.16×10^{-2}
7	Woman	-1.10×10^{-2}	1.70×10^{-3}	-6.57×10^{1}	0.00	-1.43×10^{-2}	-7.70×10^{-3}
8	Asian	6.90×10^{-2}	5.40×10^{-3}	1.27×10^{2}	0.00	5.84×10^{-2}	7.97×10^{-2}
9	Black	1.17×10^{-1}	3.30×10^{-3}	3.53×10^{2}	0.00	1.10×10^{-1}	1.23×10^{-1}
10	Native	6.78×10^{-2}	1.02×10^{-2}	6.64×10^{1}	0.00	4.78×10^{-2}	8.78×10^{-2}
11	Home Improvement	2.32×10^{-1}	3.80×10^{-3}	6.09×10^{2}	0.00	2.25×10^{-1}	2.39×10^{-1}
12	Refinancing	1.18×10^{-1}	2.80×10^{-3}	4.22×10^{2}	0.00	1.13×10^{-1}	1.24×10^{-1}
13	Cash-Out Refinancing	1.19×10^{-1}	2.20×10^{-3}	5.34×10^{2}	0.00	1.15×10^{-1}	1.24×10^{-1}
14	Other Purpose	2.61×10^{-1}	4.10×10^{-3}	6.43×10^{2}	0.00	2.54×10^{-1}	2.69×10^{-1}
15	Loan term	3.00×10^{-3}	0.00	2.91×10^{2}	0.00	3.00×10^{-3}	3.00×10^{-3}
16	log(income)	-8.93×10^{-2}	1.60×10^{-3}	-5.66×10^{2}	0.00	-9.24×10^{-2}	-8.62×10^{-2}
17	log(loan amount)	6.10×10^{-3}	1.50×10^{-3}	3.93×10^{1}	1.00×10^{-3}	3.00×10^{-3}	9.10×10^{-3}
18	log(property value)	-4.18×10^{-2}	2.00×10^{-3}	-2.06×10^{2}	0.00	-4.58×10^{-2}	-3.78×10^{-2}

Table 8: Average marginal effects ($\mathcal{M}2$)

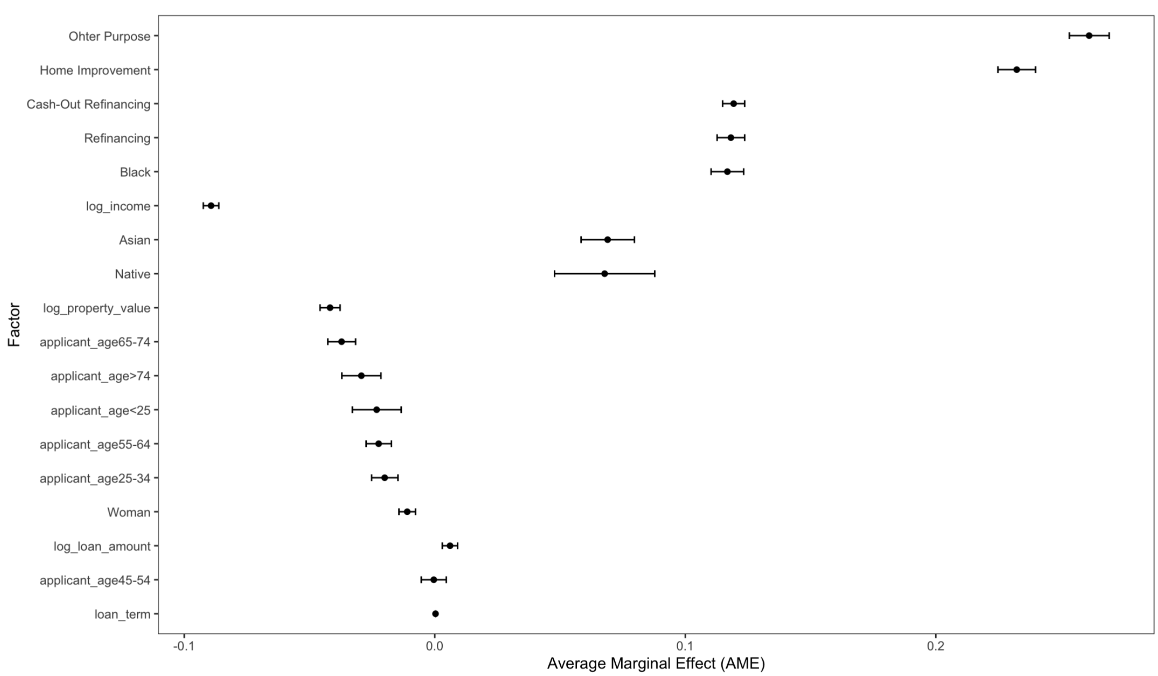

Figure 13: Average Marginal Effect Estimates with Confidence Intervals

Accuracy

	Actual	0	1
Predicted	0	40039	7712
	1	470	778

Table 9: Confusion Matrix

Extra assumptions made on our logistic model

- (H4) Every value of the vector of parameters in Θ is identified almost surely.
- (H5) $\mathbb{E}\left[\sup_{\beta\in\Theta}|f(\beta, y_i|X_i)|\right] < \infty$.
- (H6) The density $f(y_i|X_i;\beta)$ is twice continuously differentiable in β for all $\beta \in \Theta$. The support of the density does not depend on the value of β, and differentiation and integration are interchangeable.
- (H7) $(y_i)_{i\in[\![1,n]\!]}$ is iid, $\forall k \in [\![1, K]\!]$ $(x_{i,k})_{i\in[\![1,n]\!]}$ is iid.
- (H8) Θ is compact in $\mathbb{R}^{K+1}$.
- (H9) The information matrix $\mathbb{I}(\beta, y_1|X_1)$ exists and is non-singular for all $\beta \in \Theta$.

Extension to the 50 states of the US

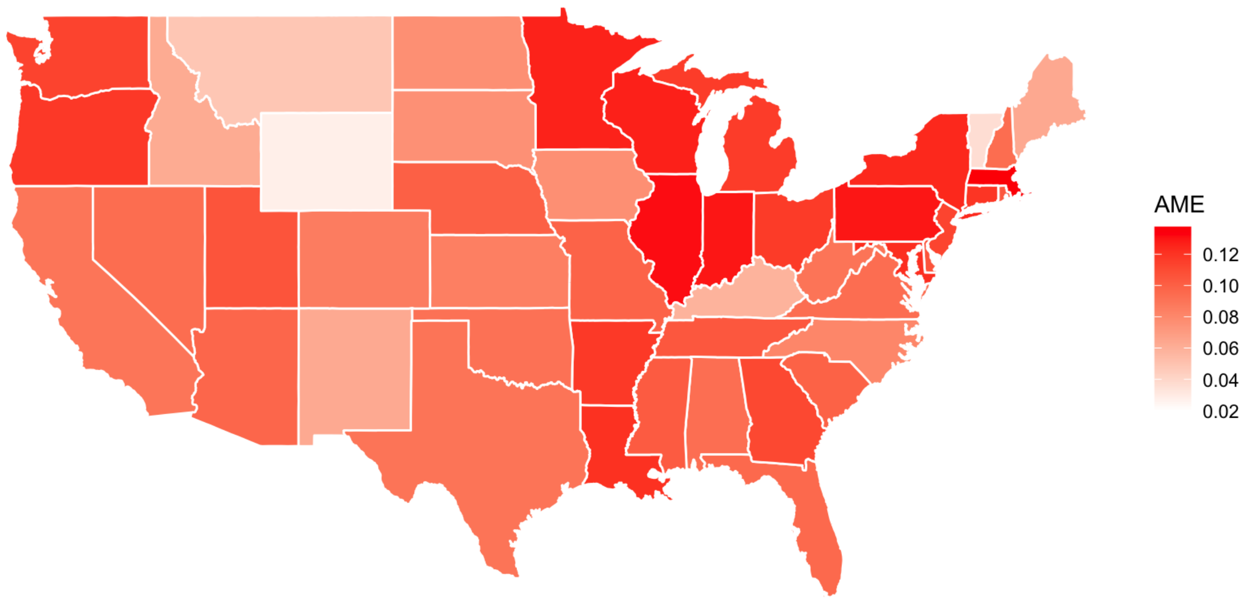

Figure 14: Average Marginal Effect Estimates on the 50 states of the United States of America

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