Are U.S. Veterans Being Racially Discriminated Against by Mortgage Lenders?

Nathan F. Rodrigues
MSc. Financial Economics with a specialization in Econometrics
Texas A&M University
Capstone Project
Data, paper and SAS code available at:
https://github.com/nathan10893/Econometrics-Capstone-Nathan-Rodrigues.git

nathan10893@hotmail.com

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Abstract

In this paper, I design statistical models to determine whether U.S. veterans are being racially discriminated against in the VA loan market. As relationships between race and mortgage lending have already been studied extensively, I use previous literature as a framework to investigate a market that has not yet been explored. Using micro loan-level data and macro data for the years 2012 – 2016, my results show that African-American, Hispanic and Asian applicants experience statistically significant racial discrimination across the United States. Not only do these groups experience higher probabilities of denial outcomes for their loan applications, but also higher loan amounts when compared with their white counterparts. Moreover, I build upon my regression models to depict how discrimination varies by U.S. state, race and ethnicity.

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1. Introduction

Racial police encounters and anti-racism protests have made Americans aware of the socioeconomic differences between black and white neighborhoods across the nation. Although these socioeconomic gaps vary from region to region, differences in certain areas appear to be much starker. For example, in the city of Baltimore, federal data claims that low incomes of black residents and their inability to qualify for a loan are the primary reasons for reductions in mortgage lending (Jason Richardson). But perhaps this is not the case. The National Community Reinvestment Coalition reports that, unlike income, the racial makeup of a neighborhood is the most significant predictor of whether a loan gets made in Baltimore (Jason Richardson).

In my capstone project, I have combined micro public housing and census data to show that racial discrimination does exist in the mortgage market. Specifically, I look at VA loans because as far as I know, there haven't been any studies or reports that exclusively focus on veteran applicants. Thus, VA loans are suitable to study not only because the data is accessible, but also because VA loans aren't so stringent with down payments, credit history and other financial status data; hence, reducing the need to control for these factors. Obviously, controlling for borrower credit data would give my project more credibility and more accurate results. But due to borrower credit data not being made publicly available in addition to this being a capstone project – not a large-scale research project – my analysis suffices in systematically determining a conclusion. With that, my findings in the VA loan market support previous literature claiming that racial discrimination does persist in the mortgage market.

1.1 What are VA Loans?

Before delving into the analysis, it is first important to get a sense of VA loans and how it differs from other types of loans. VA loans are home mortgages backed by the Department of Veterans Affairs (VA) exclusively sold to eligible service members and veterans. The VA loan guarantee comes with the following advantages: payment assistance, no private mortgage insurance premium requirement, no down payment unless sales price exceeds appraised value, reusable for purchasing, building, improving homes; or refinancing existing VA loans, direct loans, existing mortgages, etc[1][2]. More discussions about VA loans, FHA and conventional loans can be found in the next section.

2. Literature Review

As a guide for my capstone project, I drew inspiration from Ross et. al's (2016) study to help carve out my methodology. To support the discrimination hypothesis in an econometric fashion, Ross et. al used micro data in conjunction with private credit data to show that "African-American and Hispanic home buyers are 105 and 78 percent more likely to have high cost mortgages for home purchases", even after controlling for borrower and loan characteristics such as "credit score, loan to value ratio, the presence of subordinate liens, and housing and debt expenses relative to income" (Stephen L. Ross). With a sample of 2004 – 2007 data, they found that the concentration of subprime lending is evident in high poverty rate neighborhoods and

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[1] VA Home Loan Advantages I

[2] VA Home Loan Advantages II

minority neighborhoods. And while the study includes all types of loans in a sample of seven major housing markets, my project looks at VA loans all across the nation.

Their findings weren't the first to document a concentration of high cost mortgages targeted towards black and Latino neighborhoods and poor neighborhoods (Paul S. Calem) (Christopher J. Mayer) (Carolina Reid) (Lynn M. Fisher) (Kristopher S. Gerardi) (Edmiston).

In Hanson et. al (2016), their matched pair correspondence experiment uses e-mail sent out to mortgage loan originators (MLOs) inquiring assistance with home mortgages which were then used to analyze differential treatment by client race (white or African American) and by credit score. They found that MLOs were less likely to respond to inquiries from clients with African American names than clients with white names (Andrew Hanson). Moreover, when responses by credit scores were accounted for, it turns out that discrimination against African Americans was still prevalent – even in higher credit score groups (Andrew Hanson).

Campen tells us that after subprime mortgages were removed from the housing market, stringent FHA loans – loans that are sold privately and insured by the Federal Housing Administration – quickly took its place in the mortgage market. FHA loans differ from conventional loans in the sense that although it is more expensive, FHA loans do not include "predatory features" and are a substitute for those who cannot afford conventional loans[3] (Campen). As Campen states:

"… the problem of redlining became overshadowed by concern with reverse redlining, whereby areas that previously had difficulty getting any mortgage loans at all became

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[3] For more information about FHA loans and its nature, look at the **Notes on FHA (and VA) Lending** section in the [2015 Changing Patterns XXII report]()

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specifically targeted for higher-cost mortgage loans. Predatory lenders pushed loans characterized by egregiously high interest rates and fees, unconscionable features, and/or highly deceptive sales practices on minority borrowers and neighborhoods. As a result, these same borrowers and neighborhoods were disproportionately impacted by the ensuing tidal wave of foreclosures. Following the meltdown of the subprime mortgage lending industry, concerns over fairness in mortgage lending have returned to problems of access to prime mortgage loans by traditionally underserved borrowers and neighborhoods. The dramatic increase in the market share of FHA loans—that is, loans insured by the Federal Housing Administration—is an indication of reduced availability of prime mortgage loans. While FHA lending is generally done in a responsible way, FHA loans are typically more costly than prime loans and often represent a second-best option that borrowers turn to when they cannot obtain prime mortgage loans".

Campen's 2015 report on patterns of racial discrimination focused solely on FHA loans because VA loans shared approximately the same proportion of total loans to blacks, Latinos and whites (Campen). However, there was no statistical analysis in his report – merely comparisons of trends and proportions. And in regard to previous literature mentioned in this section, no analysis was conducted on VA loans specifically.

So, while race and mortgage lending has been studied extensively for years, in addition to a lack of literature on VA loans, I felt it was appropriate to construct the following hypothesis:

Are U.S. veterans being racially discriminated in the VA loan market? If so, how does this discrimination vary by U.S. state and race?

3. Data and Methodology

A majority of my data comes from the Home Mortgage Disclosure Act's (HMDA) database. I chose this database because, to the best of my knowledge, it offers the most comprehensive nationwide home mortgage loan-level microdata. Although the database contains information for the years 2007 – 2016, data prior to 2012 is in *.dat* fixed-width format without any delimiters; making it difficult for statistical software to import. Still, the dataset sufficiently comprises of approximately 7,000,000 observations for the years 2012 – 2016.

To make the analysis simple, my HMDA sample consisted of VA records based on property types that were **(1)** one-to-four family dwelling (as opposed to manufactured or multifamily dwelling), **(2)** owned and used as primary residences, **(3)** used for 3 purposes: home purchase, home improvement, refinancing and **(4)** secured by: a first lien, subordinate lien or not secured at all. Moreover, because the HMDA's census data for the years 2012 – 2016 are based on 5-year estimates, I decided to use 1-year demographic and socioeconomic estimates from other sources such as the American Community Survey Census Bureau (ACS), Bureau of Labor Statistics (BLS), United States Census Bureau, and the Federal Housing Finance Agency (FHFA). In particular, annual sex by age by veteran status by county for the population 18 years and over are from ACS; annual unemployment and labor force data by county are from BLS; annual county resident population estimates by age, sex, race, and Hispanic origin are from the United States Census Bureau; and annual county-level VA loan limits are from FHFA. After merging all the data sets by combined state and FIPS code (combined FIPS) and year, my master file consisted of approximately 2,000,000 observations.

In terms of extrapolating from an assortment of categorical, discrete and continuous data, I decided to use a logistic regression model for the binary outcome dependent variable and a linear regression model for the continuous dependent variable. Although logit and probit models yield similar results, I find it easier to interpret the coefficients from a logit model. My first option was to use a linear probability model (LPM) to approximate the Bernoulli distribution from the binary dependent variable; but when testing across different procedures in SAS the algorithms did not converge, rendering the LPM impractical for statistical analysis. When testing with a logit model across different procedures, the estimates and fit were consistent with each other. And while LPMs would have been relatively easier to interpret, I derived marginal effects of all the logit variables instead of using odds ratios as a means of interpretation.

To further enhance interpretability, some variables were transformed into natural logarithms[4]. This was applied to skewed population data from the ACS, BLS and Census Bureau estimates; HMDA's applicant income and loan amount figures; and FHFA's loan limit amounts. Apart from controlling for outliers by improving the distribution's badly-behaved tails, transforming into logarithms computes relatively larger coefficients – otherwise the estimates were smaller than one hundredth of a percentage point. Not to mention the convenience of illustrating marginal effects in percentage terms.

Since VA loans do not set caps on borrowing amounts, there are limits on the amount of liability the VA can guarantee. These loan limits vary by county since home values are dependent on location and are usually the amount a qualified veteran with full entitlement may

[4] Natural logarithms are easier to interpret in a regression context: Gelman, Andrew, and Jennifer Hill. "Data Analysis Using Regression and Multilevel/Hierarchical Models." Data Analysis Using Regression and Multilevel/Hierarchical Models, Cambridge University Press, 2016, pp. 60–61.

be able to borrow without making a down payment (U.S. Department of Veteran Affairs). According to the Department of Veteran Affairs, "the basic entitlement available to each eligible veteran is $36,000" (U.S. Department of Veteran Affairs). Lenders will generally loan up to 4 times a veteran's available entitlement without a down payment, provided the veteran is income and credit qualified and the property appraises for the asking price" (U.S. Department of Veteran Affairs). Furthermore, we should expect loan limits to positively affect the amount a financial institution is willing to lend a borrower.

Table 1 displays all the variables used in this dataset with its associated categories for nominal variables.

3.1 Key Variables

The key variables in this study are micro variables for the applicant's race and ethnicity. Even though my dataset contains macro variables for race and ethnicity, the micro variables have fewer unobservable effects relative to the macro variables. This makes sense intuitively because the macro figures are simply estimates whereas the micro figures are recorded transactions for each veteran applicant.

Micro variables are displayed on histograms in figures 1A and 1B. In figure 1A, the number of white applicant observations are significantly higher than other races. American-Indians, Asians and Native Hawaiians have the least number of observations. Similarly, in figure 1B, the number of non-Hispanic applicants are considerably larger than Hispanic applicants. However, logistic regression models proportions in this case because of the binary dependent variable, resulting in non-biased estimates in spite of the disparity of race observations. On the other hand, it could yield non-statistically significant estimates.

In figures 1C and 1D, we have box plots of the applicant's natural logarithmic loan amount against the applicant's race and ethnicity. The loan amounts are approximately 12.5 units on average for both figures and this does not depict any disparity or discrimination between races and ethnicities. Yet, the results from statistical models below suggest otherwise.

4. Modelling

4.1 Logit Model

In the first model, I use a binary outcome response where

$$y_i = \begin{cases} 1 & if\ i = loan\ accepted \\ 0 & if\ i = loan\ denied \end{cases}$$

is regressed with continuous, discrete and categorical data. The following logit model can be seen below:

$$ln\left(\frac{p}{1-p}\right) =$$

$$\beta_0 + \sum\beta_1 \cdot State + \sum\beta_2 \cdot Race + \beta_3 \cdot Year + \beta_4 \cdot ln(Applicant's\ Income) + \beta_5 \cdot Sex +$$

$$\beta_6 \cdot Ethnicity + \beta_7 \cdot Minority\ Population + \sum\beta_8 \cdot Lien\ Status + \sum\beta_9 \cdot Loan\ Purpose + \beta_{10} \cdot Co\text{-}applicant +$$

$$\beta_{11} \cdot ln(Male\ Veteran) + \beta_{12} \cdot ln(Female\ Veteran) + \beta_{13} \cdot ln(White\ Male) + \beta_{14} \cdot ln(White\ Female) +$$

$$\beta_{15} \cdot ln(Black\ Male) + \beta_{16} \cdot ln(Black\ Female) + \beta_{17} \cdot ln(Indian\text{-}American\ Male) +$$

$$\beta_{18} \cdot ln(Indian\text{-}American\ Female) + \beta_{19} \cdot ln(Asian\ American\ Male) + \beta_{20} \cdot ln(Asian\text{-}American\ Female) +$$

$$\beta_{21} \cdot ln(Native\ American\ Male) + \beta_{22} \cdot ln(Native\ American\ Female) + \beta_{23} \cdot ln(Unemployment\ Rate) +$$

$$\beta_{24} \cdot \mathit{ln(Loan\ Limit)} + \beta_{25} \cdot \mathit{ln(Applicant's\ Loan\ Amount)}$$

4.2 Linear Model

In the second model, I use the applicant's loan amount as the dependent variable because intuitively, loan amounts should explain more of the variance in the independent variables. To expedite coding in SAS, I did not specifically create dummy variables for some variables, for instance, U.S. state, as manually creating 51 (Washington, D.C. included) state dummies would be unwieldly. Instead, I ran the GLMSELECT procedure (as opposed to the GLM procedure) because of its full-rank reference parameterization which automatically creates dummies and also allows users to specify reference levels with a CLASS statement. Otherwise, the GLM procedure would produce biased estimates for the dummy variables in model **(2)**[5]. The independent variables remain the same as above:

$$\mathit{ln}(\mathit{applicant's\ loan\ amount}) =$$

$$\beta_0 + \sum\beta_1 \cdot \mathit{State} + \sum\beta_2 \cdot \mathit{Race} + \beta_3 \cdot \mathit{Year} + \beta_4 \cdot \mathit{ln(Applicant's\ Income)} + \beta_5 \cdot \mathit{Sex} +$$

$$\beta_6 \cdot \mathit{Ethnicity} + \beta_7 \cdot \mathit{Minority\ Population} + \sum\beta_8 \cdot \mathit{Lien\ Status} + \sum\beta_9 \cdot \mathit{Loan\ Purpose} + \beta_{10} \cdot \mathit{Co\text{-}applicant} +$$

$$\beta_{11} \cdot \mathit{ln(Male\ Veteran)} + \beta_{12} \cdot \mathit{ln(Female\ Veteran)} + \beta_{13} \cdot \mathit{ln(White\ Male)} + \beta_{14} \cdot \mathit{ln(White\ Female)} +$$

$$\beta_{15} \cdot \mathit{ln(Black\ Male)} + \beta_{16} \cdot \mathit{ln(Black\ Female)} + \beta_{17} \cdot \mathit{ln(Indian\text{-}American\ Male)} +$$

$$\beta_{18} \cdot \mathit{ln(Indian\text{-}American\ Female)} + \beta_{19} \cdot \mathit{ln(Asian\ American\ Male)} + \beta_{20} \cdot \mathit{ln(Asian\text{-}American\ Female)} +$$

$$\beta_{21} \cdot \mathit{ln(Native\ American\ Male)} + \beta_{22} \cdot \mathit{ln(Native\ American\ Female)} + \beta_{23} \cdot \mathit{ln(Unemployment\ Rate)} +$$

[5] More information about biased estimates from the GLM and GLMSELECT procedures can be found here: http://support.sas.com/kb/22/585.html

$\beta_{24} \cdot ln(Loan\ Limit)$

Between the logistic model and the linear model, state by race and state by ethnicity interactions are built on the model which does a considerably better job in explaining the data. The results from the next section tell us that the linear model is much more appropriate in adding interaction terms.

4.3 Linear Model with State by Race and State by Ethnicity Interactions

$$ln(applicant's\ loan\ amount)$$

$$= \beta_0 + \sum\beta_1 \cdot State + \sum\beta_2 \cdot Race + \beta_3 \cdot Year + \beta_4 \cdot ln(Applicant's\ Income) + \beta_5 \cdot Sex + \beta_6 \cdot Ethnicity + \beta_7 \cdot Minority\ Population + \sum\beta_8 \cdot Lien\ Status + \sum\beta_9 \cdot Loan\ Purpose + \beta_{10} \cdot Co\text{-}applicant + \beta_{11} \cdot ln(Male\ Veteran) + \beta_{12} \cdot ln(Female\ Veteran) + \beta_{13} \cdot ln(White\ Male) + \beta_{14} \cdot ln(White\ Female) + \beta_{15} \cdot ln(Black\ Male) + \beta_{16} \cdot ln(Black\ Female) + \beta_{17} \cdot ln(Indian\text{-}American\ Male) + \beta_{18} \cdot ln(Indian\text{-}American\ Female) + \beta_{19} \cdot ln(Asian\ American\ Male) + \beta_{20} \cdot ln(Asian\text{-}American\ Female) + \beta_{21} \cdot ln(Native\ American\ Male) + \beta_{22} \cdot ln(Native\ American\ Female) + \beta_{23} \cdot ln(Unemployment\ Rate) + \beta_{24} \cdot ln(Loan\ Limit) + \sum \beta_{25} \cdot State \cdot Race + \sum \beta_{26} \cdot State \cdot Ethnicity$$

4.4 Fixed-Effects Model

To control for location and years, a fixed-effects model was fitted. Doing this allows the model to capture the states' effects over time. However, only the GLM procedure is equipped to handle this data set – potentially yielding biased estimates[5].

$$ln(applicant's\ loan\ amount)$$

$$= \beta_0 + \sum\beta_2 \cdot Race + \beta_4 \cdot ln(Applicant's\ Income) + \beta_5 \cdot Sex + \beta_6 \cdot Ethnicity + \beta_7 \cdot Minority\ Population + \sum\beta_8 \cdot Lien\ Status + \sum\beta_9 \cdot Loan\ Purpose + \beta_{10} \cdot Co\text{-}applicant + \beta_{11} \cdot ln(Male\ Veteran) + \beta_{12} \cdot ln(Female$$

$Veteran) + \beta_{13} \cdot ln(White\ Male) + \beta_{14} \cdot ln(White\ Female) + \beta_{15} \cdot ln(Black\ Male) + \beta_{16} \cdot ln(Black$
$Female) + \beta_{17} \cdot ln(Indian\text{-}American\ Male) + \beta_{18} \cdot ln(Indian\text{-}American\ Female) + \beta_{19} \cdot ln(Asian$
$American\ Male) + \beta_{20} \cdot ln(Asian\text{-}American\ Female) + \beta_{21} \cdot ln(Native\ American\ Male) +$
$\beta_{22} \cdot ln(Native\ American\ Female) + \beta_{23} \cdot ln(Unemployment\ Rate) + \beta_{24} \cdot ln(Loan\ Limit)$

5. Analysis and Results

For model **(1)**, Table 2A contains average marginal effects for key variables in the study. In particular, when compared to white applicants, the probability of getting a loan approved decreases on average by 9.48%[6] for American Indians, 3.96% for Asians, 8.49% for African-Americans, and 5.95% for Native Hawaiians. When compared with non-Hispanics, the probability of getting a loan approved decreases on average by 0.05% for Hispanics applicants. Looking at minority populations tell us that a 1% nationwide increase in minorities decreases the average probability of getting a loan approved by 0.05%. However, a more insightful way to see how this varies by race is by looking at race by sex population.

When race by sex population is considered, a 1% increase in population of white males has the highest average probability increase (i.e. 9.42%) of getting a loan approved across the U.S. However, a 1% increase in the white female population is associated with the lowest average probability decrease (i.e. 10.74%) of getting a loan approved across the U.S. Similarly, a 1% increase in the black female population reduces the average probability of getting a loan approved by 0.5%. In other races, a percentage increase in the female population increases the average probability of getting a loan approved by 2.1%, 5.22% and 0.06% for American-Indians,

[6] SAS does not automatically produce marginal effects for the PROC LOGISTIC procedure. Marginal effects were calculated using the formula from the Econometric Sense blog. This formula is consistent with Stata's marginal effects formula for logistic regressions.

Asians and Native Hawaiians, respectively. A percentage increase in all other male population (except white) decreases the probability of getting a loan approved by 0.1% (although not statistically significant), 2.9%, 4.41% and 0.64% for African-Americans, American-Indians, Asians and Native Hawaiians, respectively.

However, the adjusted R-squared (displayed in Table 3A) is weak with a value of 0.2. That is, the model explains only 20% of the variation in the binary dependent variable.

For model **(2)**, Table 2B contains the key coefficients where correlations are consistent with previous studies on loan discrimination presented in the literature review. Specifically, when compared to white applicants, American-Indian's are subject to lower loan amounts by 1.50%[7], Asians are subject to higher loan amounts by 6.43%, African-Americans are subject to higher loan amounts by 5.44%, and Native Hawaiians are subject to higher loan amounts by 2.84%. Likewise, when compared to non-Hispanic applicants, Hispanic applicants receive higher loan amounts by 2.77%. A two-fold increase in the minority population results in a decrease in nationwide loan amounts by 0.28%. Again, it is more informative to break this down by race and sex.

Loan amounts across the U.S. have the highest increase (by 23.57%) when the Asian female population doubles. Loan amounts decrease the most (by 16.69%) when the Asian male population doubles nationwide. In the same way, a two-fold increase in the black male and black female population decreases loan amounts by 3.48% and increases loan amounts by 1.23%, respectively. The opposite relationship is observed for the American-Indian population where loan amounts increase by 2.31% as the male population doubles and decreases by 3.11% as the

[7] Formula used is from Giles, David (2011): Interpreting Dummy Variables in Semi-Logarithmic Regression Models: Exact Distributional Results

female population doubles. Correspondingly, loan amounts increase by 21.39% and 2.79% for a two-fold increase in the white male and native Hawaiian male population, respectively; while loan amounts decrease by 13.82% and 1.38% for a two-fold increase in the white female and native Hawaiian female population, respectively.

Some of these estimates on macro population, however, are contrary to my hypothesis and previous literature stated in this paper. For example, as expected, we see higher loan amounts – by 0.28% (albeit a small increase) – as the minority population doubles. However, loan amounts increase the most when the Asian female population doubles, unexpectedly followed by a doubling in the white male population, ranking whites above the remaining races instead of below.

Nonetheless, while the baseline models capture overall average relationships across the United States, it becomes more insightful to analyze racial discrimination by region, county or any other type of geographical dissection. In this case, I dissect by combined FIPS aggregated by U.S. state for regression interpretation purposes. Also, it makes more sense to focus on key micro race and ethnicity variables, not on macro race and ethnicity variables for reasons expressed in section 3.1.

When state by race and state by ethnicity interactions are added in model **(3)**, we are able to break down discrimination effects for each state. In Table 2C, only estimates with p-values less than 0.1 are included on account for saving space. We see that when compared to white applicants in WY, Asians in NY experience the highest increase in loan amounts (by 27.34%). The next race group that experiences discrimination is African-Americans; which also happens to be in NY. The estimates for American-Indians and Native Hawaiians seem slightly unconvincing since there are only a small number of these groups' observations in the data set. This is reflected in negative marginal effects for D.C. and MS. Although, the marginal effect is negative for African-Americans in D.C. as well. A large negative effect of 13.57% is somewhat perplexing but perhaps this is due to D.C.'s diverse population, high literacy rate and large number of African-Americans[8]. Still, such a large effect in the negative direction, where positive directions are consistent everywhere else for this race, should be taken with a grain of salt.

Subsequently, if we look at state by ethnicity interactions presented in Table 2D, a Hispanic veteran in NY, compared to a non-Hispanic veteran in WY, has the highest increase in loan amounts by 22.4%. Following the same logic, other state by ethnicity interactions can be interpreted this way. NY seems to have the highest effect of discrimination for both the race and ethnicity by state interactions. However, this correlation should be taken with reservations because home values are not considered and unavailable in the HMDA data set. The closest variable that traces home values in this data set would be VA loan limits; but still, it does not appropriately mimic home values.

To control for location and years, I included a fixed-effects model **(4)** that controls location by combined FIPS since the data was match-merged by this variable, not by U.S. state. This is because states cannot capture the variation of combined FIPS. For instance, poverty, minority, and household income rates (among other demographic parameters) vary within neighborhoods and offer much more explanatory power than a state variable would. Note that I did aggregate the combined FIPS variation by state for illustration purposes in the regression. The benefit that a fixed-effects model has in this circumstance is that it captures the intrastate

[8] Statistics on Washington, D.C.: US News, CSCU Study

variation over time. The regression output in Table 3D gives us a lower R-squared value, albeit identical estimates for the race variables in the linear regressions displayed in Tables 3B and 3C.

However, SAS states that the population demographic estimates are biased or not uniquely estimable. This is evident in Table 3D. As defined by SAS, this indication of an overparameterized model is the result of multiple categories in a nominal variable (thus producing biased estimates for categorical variables) and does not necessarily indicate a problem with the fitted model[9]. Be that as it may, there are no categorical variables in this model because I specifically converted them to dummy variables to explicitly avoid this error. Secondly, the output shows that the estimates are biased only for the continuous population demographic variables, which is odd since this error is supposed to occur explicitly for categorical variables. Basically, I get an error for something that does not exist. Hence, the results from the fixed-effects model are not reliable for conducting analyses.

6. Conclusion

In conclusion, my nationwide sample looks at loan application outcomes and loan amounts for 51 states (Washington, D.C. included) controlling for income, co-application status, socioeconomic and demographic data. What I have found is that veteran minorities are being discriminated against. In previous literature, studies have focused exclusively on examining African-American and Hispanic discrimination broadly either over all types of loans or in particular types besides VA loans. This is the first project, as far as I know, where VA loans are being looked at specifically. By starting off with baseline logit and linear models, interactions were added in the better fitting linear model and a fixed-effects model was considered, although

[9] Explanation of SAS errors for overparameterized models

fruitless. As it turns out, the linear model with interactions does the best job in quantifying discrimination effects not just nationwide, but also by state. From this, I have also presented states which rank the highest in terms of veteran race discrimination between 2012 and 2016.

However, it is worth pointing out the shortcomings of this project. For instance, there are many factors that have not been and could be accounted for. Amongst countless others, a few examples would be controlling for home values, foreclosure risk, and neighborhood risk.

Nevertheless, the results derived from this project are suggestive and present a nationwide screening for racial discrimination. As the Federal Reserve points out, HMDA data used in conjunction with my models do not support definitive conclusions but instead display where "differences among racial or other groups are sufficiently large to warrant further investigation"[10]. For researchers who want to delve further into my hypothesis, it would be interesting to merge applicants' credit data with HMDA data (which is what Ross et. al did in their study).

From a policy standpoint, state and local governments could impose legislature advocating for fair lending protections for veterans and military personnel. Only IL, MA, NY, OH, WA, and CO have lending protections and it would be an accomplishment to see protections all across the county.

[10] Federal Reserve: FAQ about the new HMDA data

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Figures

Figure 1A

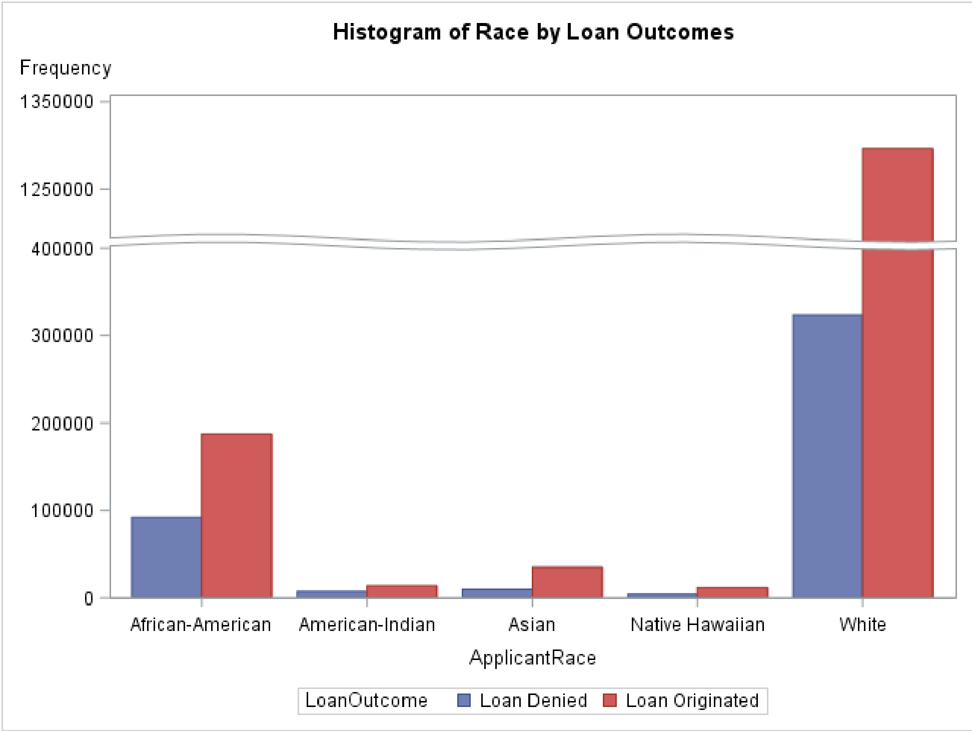


Figure 1B

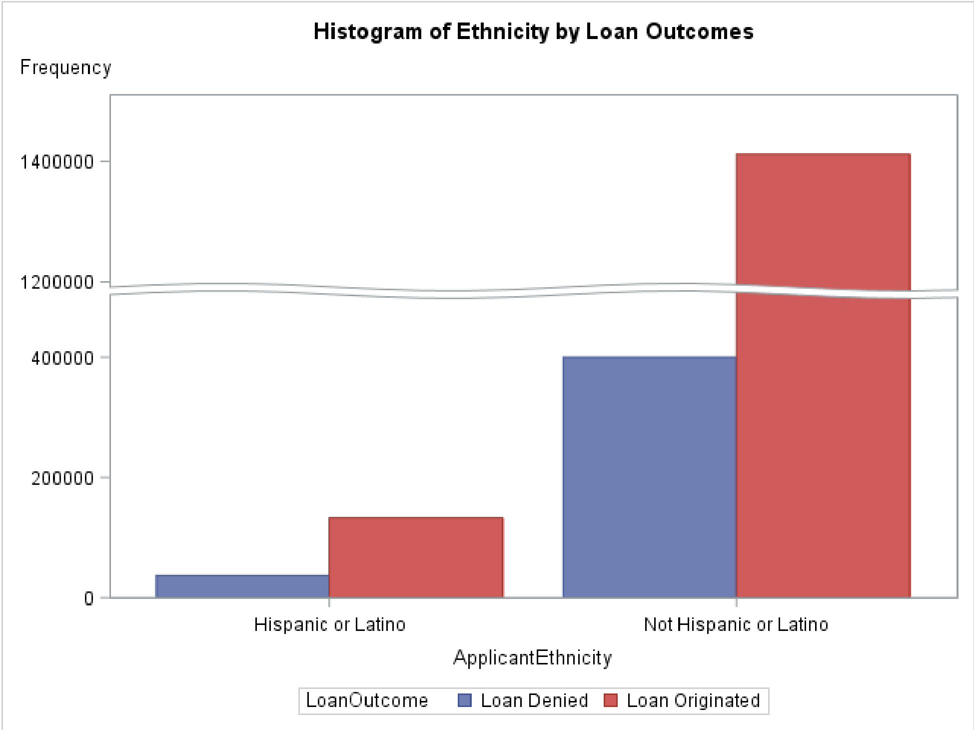


Figure 1C

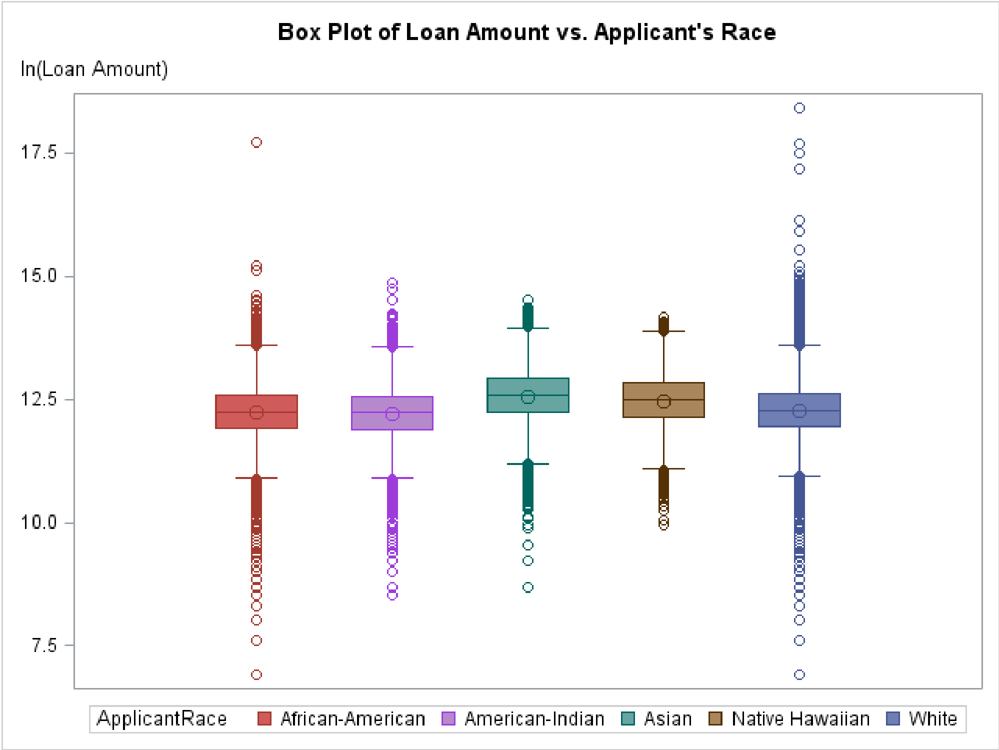
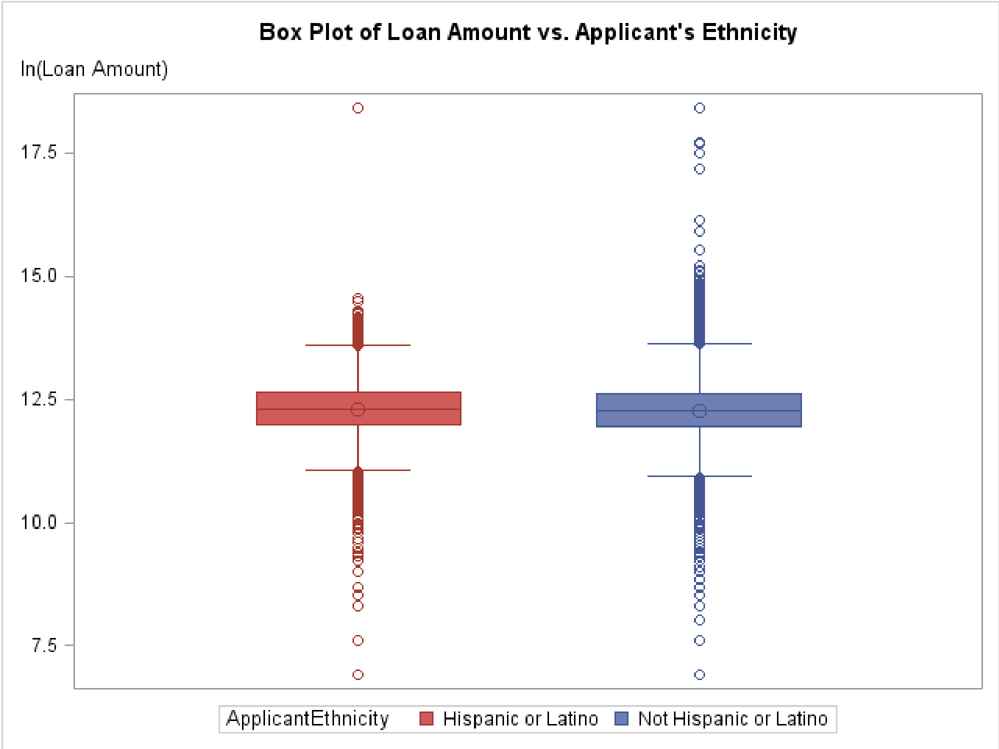


Figure 1D



Tables

Table 1: Variables and their Categories

Factors	Variables	Coding
Applicant's Mortgage Outcomes	Loan Originated Loan Denied	**1** = *Loan Originated* **0** = *Loan Denied*
Location	State	**1** = *AK*, **2** = *AL*, **3** = *AR*, . . ., **51** = *WY*
Applicant Race	American-Indian or Alaska Native Asian Black or African American Native Hawaiian or other Pacific Islander White	**1** = *American-Indian or Alaska Native* **2** = *Asian* **3** = *Black or African American* **4** = *Native Hawaiian or other Pacific Islander* **5** = *White*
Year	2012 2013 2014 2015 2016	**1** = *2012* **2** = *2013* **3** = *2014* **4** = *2015* **5** = *2016*
Applicant Sex	Male Female	**1** = *Male* **0** = *Female*
Applicant Ethnicity	Hispanic Not Hispanic	**1** = *Hispanic* **0** = *Not Hispanic*
Application Lien Status	Loan secured by a first lien Loan secured by subordinate lien Loan not secured	**1** = *Loan secured by a first lien* **2** = *Loan secured by subordinate lien* **3** = *Loan not secured*
Loan Purpose	Home Purchase Home Improvement Refinancing	**1** = *Home Purchase* **2** = *Home Improvement* **3** = *Refinancing*
Co-applicant Status	Co-applicant on application No co-applicant on application	**1** = *Co-applicant on application* **0** = *No co-applicant on application*
Log-Transformed Population Variables	Applicant's Income Applicant's Loan Amount VA Loan Limit Minority Population Male Veterans Female Veterans White Males White Females Black Males Black Females American-Indian Males American-Indian Females Asian Males Asian Females Native Hawaiian Males Native Hawaiian Females	

Table 2A: Marginal Effects for key variables in the Logistic Model

Dependent Variable	Variable	Marginal Effects	β	SE
Loan Application Binary Outcome	**Race** *(compared to White)*			
	American-Indian or Alaska Native	-9.48%	-0.720***	0.015
	Asian	-3.96%	-0.209***	0.012
	Black or African American	-8.49%	-0.619***	0.005
	Native Hawaiian or other Pacific Islander	-5.95%	-0.434***	0.019
	Ethnicity *(compared to Non-Hispanic)*			
	Hispanic	-0.05%	-0.044***	0.007
	Minority Population	-0.05%	-0.003***	0.000
	Race by Sex Population			
	White			
	Male	9.42%	0.963***	0.064
	Female	-10.74%	-1.068***	0.061
	Black			
	Male	-0.10%	-0.042**	0.014
	Female	-0.49%	-0.007	0.013
	American-Indian or Alaska Native			
	Male	-2.90%	-0.301***	0.022
	Female	2.10%	0.245***	0.022
	Asian			
	Male	-4.41%	-0.259***	0.021
	Female	5.22%	0.286***	0.022
	Native Hawaiian or other Pacific Islander			
	Male	0.64%	0.055***	0.010
	Female	0.06%	0.003	0.010
Observations		**1,982,123**		
R^2		**0.130**		
Adjusted R^2		**0.200**		
Log Likelihood		**1814703.4**		
Akaike Inf. Crit.		**1814869.4**		
Bayesian Inf. Crit.		**1815906.9**		

Table 2B: Marginal Effects for key variables in the Linear Model

Dependent Variable	Variable	Marginal Effects	β	SE
Applicant's Loan Amount	**Veteran's Race** (*compared to White)*			
	American-Indian or Alaska Native	-1.50%	-0.015***	-0.003
	Asian	6.43%	0.062***	0.019
	Black or African American	5.44%	0.053***	0.037
	Native Hawaiian or other Pacific Islander	2.84%	0.028***	0.005
	Ethnicity *(Non-Hispanic as reference)*			
	Hispanic	2.77%	0.028***	0.017
	Minority Population	-0.28%	-0.003***	-0.132

	Race by Sex Population			
	White			
	Male	21.39%	0.214***	0.482
	Female	-13.82%	-0.138***	-0.312
	Black			
	Male	-3.48%	-0.035***	-0.112
	Female	1.23%	0.012***	0.043
	American-Indian or Alaska Native			
	Male	2.31%	0.023***	0.071
	Female	-3.11%	-0.031***	-0.096
	Asian			
	Male	-16.69%	-0.167***	-0.611
	Female	23.57%	0.236***	0.837
	Native Hawaiian or other Pacific			
	Islander	2.79%	0.028***	0.097
	Male	-1.38%	-0.014***	-0.048
	Female			
Observations		1,235,484		
R^2		0.6215		
Adjusted R^2		0.6215		
Log Likelihood				
Akaike Inf. Crit.		-1752831		
Bayesian Inf. Crit.		-2987367		

Table 2C: Marginal Effects for the Linear model with State by Race Interactions (with p-values < 0.1)

Dependent Variable	State	Veteran's Race *(compared to White)*	Marginal Effects	β	SE
Applicant's Loan Amount	NJ	American-Indian or Alaska Native	15.56%	0.145*	0.073
	DC	American-Indian or Alaska Native	-16.53%	-0.181	0.1
	NY	Asian	27.34%	0.242***	0.06
	IL	Asian	14.50%	0.135*	0.06
	PA	Asian	14.41%	0.135*	0.06
	MI	Asian	11.02%	0.105	0.063
	OH	Asian	10.76%	0.102	0.061
	NY	Black or African American	15.95%	0.148***	0.032
	AR	Black or African American	11.75%	0.111***	0.032
	GA	Black or African American	9.68%	0.092***	0.031
	WV	Black or African American	9.66%	0.092*	0.038
	MD	Black or African American	8.28%	0.080*	0.031
	MS	Black or African American	8.06%	0.078*	0.032
	AL	Black or African American	6.93%	0.067*	0.031
	IN	Black or African American	5.93%	0.058	0.032
	TX	Black or African American	5.63%	0.055	0.031
	DC	Black or African American	-13.57%	-0.146***	0.036

	NY	Native Hawaiian or other Pacific Islander	16.84%	0.156	0.085
	MS	Native Hawaiian or other Pacific Islander	-18.20%	-0.201	0.108
Observations **R^2** **Adjusted R^2** **Log Likelihood** **Akaike Inf. Crit.** **Bayesian Inf. Crit.**		1,235,484 0.6226 0.6225 -1755890 -2991374			

Table 2D: Marginal Effects for the Linear model with State by Ethnicity Interactions (with p-values < 0.1)

Dependent Variable	State	Veteran's Ethnicity *(compared to Non-Hispanic)*	Marginal Effects	β	SE
Applicant's Loan Amount	NY	Hispanic	22.40%	0.202***	0.025
	WV	Hispanic	13.22%	0.124*	0.046
	FL	Hispanic	10.25%	0.098***	0.024
	IL	Hispanic	10.14%	0.097***	0.024
	ME	Hispanic	8.46%	0.081	0.049
	IN	Hispanic	8.46%	0.081**	0.026
	DC	Hispanic	7.12%	0.069	0.040
	CA	Hispanic	5.52%	0.054*	0.024
	WI	Hispanic	5.42%	0.053	0.028
	TX	Hispanic	4.77%	0.047*	0.024
	MD	Hispanic	4.70%	0.046	0.024
	NM	Hispanic	4.43%	0.043	0.024
Observations **R^2** **Adjusted R^2** **Log Likelihood** **Akaike Inf. Crit.** **Bayesian Inf. Crit.**		1,235,484 0.6226 0.6225 -1755890 -2991374			

Table 3A: Logistic Regression Summary Output

Dependent Variable	Variables	Estimates	SE	P-values
Loan Application Outcomes	**Intercept**	0.352	0.615	0.567
	State			
	AK	-0.080	0.059	0.172
	AL	-0.371	0.051	<.0001

		AR	-0.270	0.053	<.0001
		AZ	-0.294	0.051	<.0001
		CA	-0.284	0.051	<.0001
		CO	-0.082	0.050	0.104
		CT	-0.730	0.054	<.0001
		DC	-0.214	0.073	0.004
		DE	-0.410	0.056	<.0001
		FL	-0.640	0.050	<.0001
		GA	-0.472	0.051	<.0001
		HI	-0.512	0.062	<.0001
		IA	-0.381	0.056	<.0001
		ID	-0.357	0.055	<.0001
		IL	-0.400	0.052	<.0001
		IN	-0.482	0.052	<.0001
		KS	-0.281	0.054	<.0001
		KY	-0.428	0.053	<.0001
		LA	-0.374	0.052	<.0001
		MA	-0.584	0.052	<.0001
		MD	-0.411	0.051	<.0001
		ME	-0.846	0.057	<.0001
		MI	-0.642	0.051	<.0001
		MN	-0.203	0.053	0.000
		MO	-0.360	0.052	<.0001
		MS	-0.390	0.055	<.0001
		MT	-0.402	0.059	<.0001
		NC	-0.313	0.050	<.0001
		ND	0.162	0.070	0.022
		NE	-0.028	0.056	0.621
		NH	-0.782	0.057	<.0001
		NJ	-0.728	0.053	<.0001
		NM	-0.312	0.054	<.0001
		NV	-0.335	0.053	<.0001
		NY	-0.614	0.051	<.0001
		OH	-0.566	0.051	<.0001
		OK	-0.229	0.053	<.0001
		OR	-0.365	0.052	<.0001
		PA	-0.655	0.051	<.0001
		RI	-0.477	0.062	<.0001
		SC	-0.439	0.051	<.0001
		SD	0.113	0.069	0.102
		TN	-0.362	0.051	<.0001
		TX	-0.401	0.050	<.0001
		UT	-0.099	0.054	0.070

	VA	-0.159	0.051	0.002
	VT	-0.371	0.121	0.002
	WA	-0.320	0.051	<.0001
	WI	-0.531	0.052	<.0001
	WV	-0.480	0.061	<.0001
	WY		*reference*	
	Race			
	American-Indian	-0.645	0.016	<.0001
	Asian	-0.270	0.013	<.0001
	Black or African-American	-0.579	0.006	<.0001
	Native Hawaiian	-0.405	0.020	<.0001
	White		*reference*	
	Year			
	2012	0.084	0.008	<.0001
	2013	0.045	0.007	<.0001
	2014	0.008	0.006	0.169
	2015	0.068	0.005	<.0001
	2016		*reference*	
	Sex			
	Male	0.079	0.006	<.0001
	Female		*reference*	
	Ethnicity			
	Hispanic	-0.168	0.007	<.0001
	Non-Hispanic		*reference*	
	Co-Application Status			
	Co-Applicant Present	0.175	0.004	<.0001
	Co-Applicant Not Present		*reference*	
	Lien			
	Secured by First Lien	-0.220	0.525	0.675
	Secured by Second Lien	-1.634	0.543	0.003
	Not Secured		*reference*	
	Loan purpose			
	Home Purchase	1.632	0.004	<.0001
	Home Improvements	0.570	0.013	<.0001
	Refinancing		*reference*	
	Applicant's Loan Amount	-0.070	0.005	<.0001
	Applicant's Income	0.601	0.004	<.0001
	Population Demographics			
	Minority Population	-0.003	0.000	<.0001
	Male Veterans	0.000	0.012	0.995
	Female Veterans	0.103	0.006	<.0001
	White Males	0.642	0.068	<.0001
	White Females	-0.732	0.065	<.0001

	Black or African-American Males	-0.006	0.015	0.666
	Black or African-American Females	-0.034	0.013	0.012
	American-Indian Males	-0.198	0.023	<.0001
	American-Indian Females	0.143	0.023	<.0001
	Asian Males	-0.300	0.022	<.0001
	Asian Females	0.355	0.024	<.0001
	Native Hawaiian Males	0.044	0.011	<.0001
	Native Hawaiian Females	0.004	0.011	0.724
	Unemployment Rates	-0.022	0.002	<.0001
	VA Loan Limits	-0.365	0.025	<.0001
R-Square			**0.130**	
Adjusted R-Square			**0.200**	
AIC			**1814869.4**	
BIC			**1815906.9**	

Table 3B: Linear Regression Summary Output

Dependent Variable	Variables	Estimates	SE	P-values
Loan Amounts	**Intercept**	-1.999	0.058	<.0001
	State			
	AK	-0.170	0.007	<.0001
	AL	-0.151	0.006	<.0001
	AR	-0.283	0.006	<.0001
	AZ	-0.119	0.006	<.0001
	CA	0.084	0.006	<.0001
	CO	0.008	0.006	0.156
	CT	-0.126	0.007	<.0001
	DC	0.297	0.010	<.0001
	DE	0.073	0.007	<.0001
	FL	-0.119	0.006	<.0001
	GA	-0.123	0.006	<.0001
	HI	0.102	0.008	<.0001
	IA	-0.339	0.007	<.0001
	ID	-0.189	0.006	<.0001
	IL	-0.280	0.006	<.0001
	IN	-0.333	0.006	<.0001
	KS	-0.320	0.006	<.0001
	KY	-0.267	0.006	<.0001
	LA	-0.092	0.006	<.0001
	MA	-0.023	0.006	0.000

	MD	0.043	0.006	<.0001
	ME	-0.206	0.007	<.0001
	MI	-0.351	0.006	<.0001
	MN	-0.189	0.006	<.0001
	MO	-0.289	0.006	<.0001
	MS	-0.192	0.007	<.0001
	MT	-0.078	0.007	<.0001
	NC	-0.120	0.006	<.0001
	ND	-0.100	0.008	<.0001
	NE	-0.323	0.006	<.0001
	NH	-0.182	0.007	<.0001
	NJ	-0.185	0.006	<.0001
	NM	-0.059	0.006	<.0001
	NV	-0.085	0.006	<.0001
	NY	-0.284	0.006	<.0001
	OH	-0.355	0.006	<.0001
	OK	-0.266	0.006	<.0001
	OR	-0.029	0.006	<.0001
	PA	-0.247	0.006	<.0001
	RI	-0.060	0.008	<.0001
	SC	-0.069	0.006	<.0001
	SD	-0.159	0.008	<.0001
	TN	-0.151	0.006	<.0001
	TX	-0.211	0.006	<.0001
	UT	-0.195	0.006	<.0001
	VA	0.012	0.006	0.033
	VT	-0.105	0.016	<.0001
	WA	-0.064	0.006	<.0001
	WI	-0.327	0.006	<.0001
	WV	-0.254	0.008	<.0001
	WY		*reference*	
	Race			
	American-Indian	-0.015	0.003	<.0001
	Asian	0.062	0.002	<.0001
	Black or African-American	0.053	0.001	<.0001
	Native Hawaiian	0.028	0.003	<.0001
	White		*reference*	
	Years			
	2012	-0.031	0.001	<.0001
	2013	-0.021	0.001	<.0001
	2014	-0.035	0.001	<.0001
	2015	-0.021	0.001	<.0001
	2016		*reference*	

	Sex			
	Male	0.009	0.001	<.0001
	Female		*reference*	
	Ethnicity			
	Hispanic	0.027	0.001	<.0001
	Non-Hispanic		*reference*	
	Co-Application Status			
	Co-Applicant Present	0.001	0.001	0.265
	Co-Applicant Not Present		*reference*	
	Applicant's Income	0.545	0.001	<.0001
	Population Demographics			
	Minority Population	-0.003	0.000	<.0001
	Male Veterans	-0.129	0.002	<.0001
	Female Veterans	0.019	0.001	<.0001
	White Males	0.214	0.010	<.0001
	White Females	-0.138	0.009	<.0001
	Black or African-American Males	-0.035	0.002	<.0001
	Black or African-American Females	0.012	0.002	<.0001
	American-Indian Males	0.023	0.004	<.0001
	American-Indian Females	-0.031	0.003	<.0001
	Asian Males	-0.167	0.003	<.0001
	Asian Females	0.236	0.003	<.0001
	Native Hawaiian Males	0.028	0.002	<.0001
	Native Hawaiian Females	-0.014	0.002	<.0001
	Unemployment Rates	-0.020	0.000	<.0001
	VA Loan Limits	0.502	0.004	<.0001
Adjusted R-Square			**0.622**	
AIC			**-1752831**	
BIC			**-2988315**	

*significant at p < 0.05; ** significant at p < 0.005; *** significant at p < 0.001*

Table 3C: Linear Regression with Interactions Summary Output

Dependent Variable	Variables		Estimates	SE	P-values
Loan Amounts	**Intercept**		-1.846	0.058	<.0001
	State*Race Interactions				
	AK	American-Indian	0.085	0.069	0.217
	AK	Asian	0.022	0.060	0.714
	AK	Black or African-American	0.014	0.035	0.682

		AK	Native Hawaiian	0.108	0.085	0.204
		AL	American-Indian	0.037	0.070	0.593
		AL	Asian	0.067	0.062	0.287
		AL	Black or African-American	0.067	0.031	0.033
		AL	Native Hawaiian	-0.028	0.089	0.752
		AR	American-Indian	0.051	0.071	0.469
		AR	Asian	0.050	0.067	0.456
		AR	Black or African-American	0.111	0.032	0.001
		AR	Native Hawaiian	0.148	0.096	0.122
		AZ	American-Indian	0.065	0.067	0.328
		AZ	Asian	0.047	0.059	0.425
		AZ	Black or African-American	0.023	0.032	0.465
		AZ	Native Hawaiian	0.046	0.082	0.571
		CA	American-Indian	0.048	0.066	0.467
		CA	Asian	0.087	0.058	0.131
		CA	Black or African-American	0.015	0.031	0.641
		CA	Native Hawaiian	0.083	0.080	0.302
		CO	American-Indian	0.053	0.067	0.425
		CO	Asian	0.036	0.059	0.537
		CO	Black or African-American	0.011	0.032	0.717
		CO	Native Hawaiian	0.035	0.081	0.666
		CT	American-Indian	0.094	0.077	0.226
		CT	Asian	0.062	0.066	0.345
		CT	Black or African-American	-0.053	0.034	0.120
		CT	Native Hawaiian	0.013	0.100	0.897
		DC	American-Indian	-0.181	0.100	0.070
		DC	Asian	0.001	0.071	0.988
		DC	Black or African-American	-0.146	0.036	<.0001
		DC	Native Hawaiian	0.085	0.121	0.482
		DE	American-Indian	0.058	0.080	0.472
		DE	Asian	-0.010	0.070	0.889
		DE	Black or African-American	0.010	0.033	0.762
		DE	Native Hawaiian	0.146	0.107	0.173
		FL	American-Indian	0.044	0.066	0.507
		FL	Asian	0.040	0.058	0.491
		FL	Black or African-American	0.048	0.031	0.127
		FL	Native Hawaiian	0.036	0.081	0.651
		GA	American-Indian	0.047	0.067	0.481
		GA	Asian	0.031	0.059	0.593
		GA	Black or African-American	0.092	0.031	0.003
		GA	Native Hawaiian	0.047	0.082	0.568
		HI	American-Indian	0.055	0.070	0.434
		HI	Asian	0.004	0.058	0.947

		HI	Black or African-American	-0.021	0.033	0.518
		HI	Native Hawaiian	0.001	0.081	0.985
		IA	American-Indian	0.044	0.084	0.601
		IA	Asian	0.034	0.070	0.622
		IA	Black or African-American	0.051	0.037	0.172
		IA	Native Hawaiian	0.014	0.120	0.909
		ID	American-Indian	0.068	0.074	0.359
		ID	Asian	-0.040	0.068	0.558
		ID	Black or African-American	-0.028	0.047	0.553
		ID	Native Hawaiian	0.059	0.093	0.523
		IL	American-Indian	0.035	0.071	0.617
		IL	Asian	0.135	0.060	0.023
		IL	Black or African-American	0.005	0.032	0.885
		IL	Native Hawaiian	0.058	0.085	0.495
		IN	American-Indian	0.114	0.072	0.113
		IN	Asian	0.074	0.063	0.244
		IN	Black or African-American	0.058	0.032	0.071
		IN	Native Hawaiian	-0.012	0.091	0.893
		KS	American-Indian	0.038	0.070	0.590
		KS	Asian	0.038	0.061	0.532
		KS	Black or African-American	0.013	0.034	0.709
		KS	Native Hawaiian	0.038	0.094	0.682
		KY	American-Indian	0.108	0.079	0.171
		KY	Asian	0.076	0.066	0.252
		KY	Black or African-American	0.014	0.032	0.660
		KY	Native Hawaiian	0.034	0.092	0.716
		LA	American-Indian	0.011	0.072	0.877
		LA	Asian	-0.005	0.064	0.939
		LA	Black or African-American	0.015	0.032	0.629
		LA	Native Hawaiian	-0.037	0.091	0.686
		MA	American-Indian	0.103	0.077	0.182
		MA	Asian	0.071	0.062	0.247
		MA	Black or African-American	0.019	0.033	0.575
		MA	Native Hawaiian	0.071	0.094	0.448
		MD	American-Indian	0.094	0.068	0.168
		MD	Asian	0.058	0.058	0.321
		MD	Black or African-American	0.080	0.031	0.011
		MD	Native Hawaiian	0.072	0.082	0.386
		ME	American-Indian	0.081	0.083	0.326
		ME	Asian	-0.036	0.083	0.662
		ME	Black or African-American	0.056	0.055	0.310
		ME	Native Hawaiian	0.071	0.117	0.547
		MI	American-Indian	0.040	0.070	0.566

		MI	Asian	0.105	0.063	0.097
		MI	Black or African-American	0.000	0.032	0.995
		MI	Native Hawaiian	0.055	0.090	0.537
		MN	American-Indian	0.047	0.073	0.518
		MN	Asian	0.071	0.061	0.244
		MN	Black or African-American	-0.006	0.034	0.858
		MN	Native Hawaiian	0.023	0.093	0.805
		MO	American-Indian	0.109	0.071	0.124
		MO	Asian	0.037	0.063	0.560
		MO	Black or African-American	-0.014	0.032	0.658
		MO	Native Hawaiian	0.034	0.089	0.706
		MS	American-Indian	0.106	0.079	0.183
		MS	Asian	0.058	0.071	0.415
		MS	Black or African-American	0.078	0.032	0.016
		MS	Native Hawaiian	-0.201	0.108	0.063
		MT	American-Indian	-0.009	0.073	0.900
		MT	Asian	0.035	0.079	0.656
		MT	Black or African-American	-0.005	0.049	0.918
		MT	Native Hawaiian	0.030	0.104	0.776
		NC	American-Indian	0.069	0.067	0.305
		NC	Asian	0.041	0.059	0.484
		NC	Black or African-American	0.028	0.031	0.377
		NC	Native Hawaiian	0.015	0.082	0.858
		ND	American-Indian	0.025	0.084	0.767
		ND	Asian	-0.044	0.076	0.561
		ND	Black or African-American	0.030	0.046	0.514
		ND	Native Hawaiian	0.154	0.118	0.190
		NE	American-Indian	0.090	0.076	0.239
		NE	Asian	0.056	0.064	0.380
		NE	Black or African-American	0.011	0.035	0.755
		NE	Native Hawaiian	0.020	0.092	0.831
		NH	American-Indian	0.054	0.084	0.517
		NH	Asian	0.029	0.078	0.706
		NH	Black or African-American	-0.013	0.048	0.779
		NH	Native Hawaiian	0.057	0.106	0.589
		NJ	American-Indian	0.145	0.073	0.047
		NJ	Asian	0.061	0.060	0.308
		NJ	Black or African-American	0.012	0.032	0.703
		NJ	Native Hawaiian	0.027	0.087	0.752
		NM	American-Indian	0.069	0.068	0.307
		NM	Asian	-0.002	0.064	0.979
		NM	Black or African-American	-0.009	0.034	0.791
		NM	Native Hawaiian	0.028	0.088	0.753

	NV	American-Indian	0.087	0.069	0.204
	NV	Asian	0.074	0.058	0.204
	NV	Black or African-American	0.023	0.032	0.463
	NV	Native Hawaiian	0.090	0.081	0.269
	NY	American-Indian	0.057	0.070	0.414
	NY	Asian	0.242	0.060	<.0001
	NY	Black or African-American	0.148	0.032	<.0001
	NY	Native Hawaiian	0.156	0.085	0.067
	OH	American-Indian	0.006	0.069	0.936
	OH	Asian	0.102	0.061	0.092
	OH	Black or African-American	-0.026	0.032	0.401
	OH	Native Hawaiian	0.082	0.086	0.340
	OK	American-Indian	0.062	0.067	0.356
	OK	Asian	0.037	0.061	0.545
	OK	Black or African-American	0.044	0.032	0.171
	OK	Native Hawaiian	-0.024	0.086	0.781
	OR	American-Indian	0.065	0.068	0.340
	OR	Asian	0.046	0.060	0.443
	OR	Black or African-American	-0.004	0.035	0.901
	OR	Native Hawaiian	0.061	0.085	0.470
	PA	American-Indian	0.071	0.069	0.307
	PA	Asian	0.135	0.060	0.026
	PA	Black or African-American	-0.010	0.032	0.749
	PA	Native Hawaiian	0.045	0.087	0.600
	RI	American-Indian	0.070	0.096	0.469
	RI	Asian	0.013	0.077	0.867
	RI	Black or African-American	-0.057	0.043	0.185
	RI	Native Hawaiian	0.129	0.115	0.263
	SC	American-Indian	0.026	0.068	0.706
	SC	Asian	0.063	0.060	0.295
	SC	Black or African-American	0.024	0.031	0.446
	SC	Native Hawaiian	0.027	0.084	0.752
	SD	American-Indian	0.064	0.080	0.424
	SD	Asian	0.022	0.082	0.783
	SD	Black or African-American	0.049	0.048	0.308
	SD	Native Hawaiian	-0.023	0.115	0.842
	TN	American-Indian	0.059	0.068	0.391
	TN	Asian	-0.008	0.060	0.895
	TN	Black or African-American	0.038	0.031	0.225
	TN	Native Hawaiian	-0.006	0.083	0.940
	TX	American-Indian	0.073	0.066	0.265
	TX	Asian	0.058	0.058	0.321
	TX	Black or African-American	0.055	0.031	0.079

	TX	Native Hawaiian	0.057	0.080	0.478
	UT	American-Indian	0.043	0.071	0.545
	UT	Asian	0.019	0.061	0.752
	UT	Black or African-American	-0.010	0.036	0.779
	UT	Native Hawaiian	0.094	0.086	0.274
	VA	American-Indian	0.050	0.067	0.456
	VA	Asian	0.029	0.058	0.611
	VA	Black or African-American	0.016	0.031	0.607
	VA	Native Hawaiian	0.043	0.081	0.595
	VT	American-Indian	-0.009	0.163	0.957
	VT	Asian	-0.018	0.182	0.921
	VT	Black or African-American	0.118	0.154	0.443
	VT	Native Hawaiian	0.000	-	-
	WA	American-Indian	0.055	0.066	0.408
	WA	Asian	0.041	0.058	0.482
	WA	Black or African-American	-0.017	0.032	0.584
	WA	Native Hawaiian	0.040	0.081	0.618
	WI	American-Indian	0.005	0.073	0.946
	WI	Asian	-0.030	0.064	0.636
	WI	Black or African-American	-0.034	0.034	0.305
	WI	Native Hawaiian	0.016	0.095	0.870
	WV	American-Indian	0.090	0.088	0.308
	WV	Asian	0.095	0.087	0.273
	WV	Black or African-American	0.092	0.038	0.015
	WV	Native Hawaiian	-0.067	0.128	0.598
	WY	White		*reference*	
	State*Ethnicity				
	AK	Hispanic	0.011	0.028	0.698
	AL	Hispanic	0.029	0.027	0.279
	AR	Hispanic	0.025	0.029	0.390
	AZ	Hispanic	0.032	0.024	0.178
	CA	Hispanic	0.054	0.024	0.023
	CO	Hispanic	0.022	0.024	0.349
	CT	Hispanic	-0.021	0.027	0.439
	DC	Hispanic	0.069	0.040	0.088
	DE	Hispanic	0.035	0.031	0.269
	FL	Hispanic	0.098	0.024	<.0001
	GA	Hispanic	0.036	0.024	0.143
	HI	Hispanic	0.002	0.026	0.948
	IA	Hispanic	0.031	0.032	0.330
	ID	Hispanic	-0.015	0.029	0.600
	IL	Hispanic	0.097	0.024	<.0001
	IN	Hispanic	0.081	0.026	0.002

	KS Hispanic	-0.004	0.027	0.882
	KY Hispanic	0.027	0.029	0.344
	LA Hispanic	0.014	0.027	0.598
	MA Hispanic	0.003	0.026	0.898
	MD Hispanic	0.046	0.024	0.061
	ME Hispanic	0.081	0.049	0.099
	MI Hispanic	0.032	0.027	0.229
	MN Hispanic	0.020	0.029	0.493
	MO Hispanic	0.036	0.028	0.195
	MS Hispanic	0.014	0.033	0.666
	MT Hispanic	0.042	0.037	0.250
	NC Hispanic	0.024	0.024	0.314
	ND Hispanic	0.046	0.042	0.266
	NE Hispanic	0.013	0.029	0.649
	NH Hispanic	0.031	0.034	0.359
	NJ Hispanic	0.039	0.025	0.120
	NM Hispanic	0.043	0.024	0.077
	NV Hispanic	0.020	0.025	0.406
	NY Hispanic	0.202	0.025	<.0001
	OH Hispanic	0.027	0.026	0.290
	OK Hispanic	0.020	0.026	0.425
	OR Hispanic	0.027	0.026	0.302
	PA Hispanic	0.030	0.025	0.230
	RI Hispanic	-0.032	0.034	0.346
	SC Hispanic	0.026	0.025	0.293
	SD Hispanic	0.038	0.042	0.366
	TN Hispanic	0.016	0.025	0.514
	TX Hispanic	0.047	0.024	0.048
	UT Hispanic	0.015	0.026	0.552
	VA Hispanic	0.029	0.024	0.219
	VT Hispanic	0.055	0.091	0.546
	WA Hispanic	0.019	0.024	0.424
	WI Hispanic	0.053	0.028	0.062
	WV Hispanic	0.124	0.046	0.007
	WY Non-Hispanic		*reference*	
	State			
	AK	-0.166	0.007	<.0001
	AL	-0.161	0.006	<.0001
	AR	-0.296	0.007	<.0001
	AZ	-0.121	0.006	<.0001
	CA	0.081	0.006	<.0001
	CO	0.008	0.006	0.186
	CT	-0.117	0.007	<.0001

	DC	0.355	0.012	<.0001
	DE	0.076	0.008	<.0001
	FL	-0.131	0.006	<.0001
	GA	-0.145	0.006	<.0001
	HI	0.128	0.008	<.0001
	IA	-0.344	0.007	<.0001
	ID	-0.191	0.007	<.0001
	IL	-0.284	0.006	<.0001
	IN	-0.341	0.006	<.0001
	KS	-0.319	0.007	<.0001
	KY	-0.269	0.007	<.0001
	LA	-0.088	0.007	<.0001
	MA	-0.025	0.007	0.000
	MD	0.029	0.006	<.0001
	ME	-0.213	0.008	<.0001
	MI	-0.352	0.006	<.0001
	MN	-0.191	0.006	<.0001
	MO	-0.289	0.006	<.0001
	MS	-0.205	0.007	<.0001
	MT	-0.082	0.007	<.0001
	NC	-0.120	0.006	<.0001
	ND	-0.102	0.008	<.0001
	NE	-0.325	0.007	<.0001
	NH	-0.186	0.007	<.0001
	NJ	-0.181	0.007	<.0001
	NM	-0.058	0.007	<.0001
	NV	-0.088	0.006	<.0001
	NY	-0.315	0.006	<.0001
	OH	-0.354	0.006	<.0001
	OK	-0.268	0.006	<.0001
	OR	-0.033	0.006	<.0001
	PA	-0.249	0.006	<.0001
	RI	-0.057	0.008	<.0001
	SC	-0.069	0.006	<.0001
	SD	-0.162	0.008	<.0001
	TN	-0.153	0.006	<.0001
	TX	-0.217	0.006	<.0001
	UT	-0.196	0.007	<.0001
	VA	0.018	0.006	0.003
	VT	-0.111	0.016	<.0001
	WA	-0.063	0.006	<.0001
	WI	-0.327	0.006	<.0001
	WV	-0.265	0.008	<.0001

	WY		*reference*	
	Race			
	American-Indian	-0.072	0.065	0.269
	Asian	0.005	0.058	0.936
	Black or African-American	0.017	0.031	0.593
	Native Hawaiian	-0.024	0.080	0.765
	White		*reference*	
	Year			
	2012	-0.031	0.001	<.0001
	2013	-0.021	0.001	<.0001
	2014	-0.035	0.001	<.0001
	2015	-0.021	0.001	<.0001
	2016		*reference*	
	Sex			
	Male	0.009	0.001	<.0001
	Female		*reference*	
	Ethnicity			
	Hispanic	-0.020	0.024	0.385
	Non-Hispanic		*reference*	
	Co-Applicant Status			
	Present	0.001	0.001	0.312
	Not Present		*reference*	
	Applicant's Income	0.545	0.001	<.0001
	Population Demographics			
	Minority Population	-0.003	0.000	<.0001
	Male Veterans	-0.126	0.002	<.0001
	Female Veterans	0.019	0.001	<.0001
	White Males	0.213	0.010	<.0001
	White Females	-0.138	0.009	<.0001
	Black or African-American Males	-0.036	0.002	<.0001
	Black or African-American Females	0.013	0.002	<.0001
	American-Indian Males	0.020	0.004	<.0001
	American-Indian Females	-0.029	0.003	<.0001
	Asian Males	-0.168	0.003	<.0001
	Asian Females	0.237	0.003	<.0001
	Native Hawaiian Males	0.029	0.002	<.0001
	Native Hawaiian Females	-0.015	0.002	<.0001
	Unemployment Rates	-0.020	0.000	<.0001
	VA Loan Limits	0.490	0.004	<.0001
R-Square			**0.623**	
Adjusted R-Square			**0.623**	
AIC			**-1755890**	
BIC			**-2991374**	

*significant at p < 0.05; ** significant at p < 0.005; *** significant at p < 0.001*

Table 3D: Fixed-Effects Linear Regression Summary Output

Dependent Variable	Independent Variables	Estimates	SE	P-values
Loan Amounts	**Race**			
	American-Indian	-0.014	0.002	<.0001
	Asian	0.063	0.002	<.0001
	Black or African-American	0.050	0.001	<.0001
	Native Hawaiian	0.034	0.003	<.0001
	White		*reference*	
	Sex			
	Male	-0.012	0.001	<.0001
	Female		*reference*	
	Ethnicity			
	Hispanic	0.012	0.001	<.0001
	Non-Hispanic		*reference*	
	Co-Application Status			
	Co-Applicant Present	0.021	0.001	<.0001
	Co-Applicant Not Present		*reference*	
	Lien			
	Secured by First Lien	3.319	0.071	<.0001
	Secured by Second Lien	2.322	0.075	<.0001
	Not Secured		*reference*	
	Loan Purpose			
	Home Purchase	0.106	0.001	<.0001
	Home Improvement	-0.014	0.002	<.0001
	Refinance		*reference*	
	Applicant's Income	0.402	0.000	<.0001
	Population Demographics			
	Minority Population	-0.005	0.000	<.0001
	Male Veterans	0.000	-	-
	Female Veterans	0.000	-	-
	White Males	0.000	-	-
	White Females	0.000	-	-
	Black or African-American Males	0.000	-	-
	Black or African-American Females	0.000	-	-
	American-Indian Males	0.000	-	-
	American-Indian Females	0.000	-	-

	Asian Males	0.000	-	-
	Asian Females	0.000	-	-
	Native Hawaiian Males	0.000	-	-
	Native Hawaiian Females	0.000	-	-
	Unemployment Rates	0.000	-	-
	VA Loan Limits	0.000	-	-
R-Square			**0.579**	
AIC			**-**	
BIC			**-**	

*significant at $p < 0.05$; ** significant at $p < 0.005$; *** significant at $p < 0.001$*