Characteristics of Recent Mexican Immigrants to California, USA, that Influence Household Income

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Section 1: Introduction

1.1 Objective

We are aiming to build a model to determine which characteristics of Mexican immmigrants to the United States, specifically California, well-explain variation in household income.

1.2 Description of Dataset

The dataset is from The Mexican Migration Project (MMP, *see References below for confidentiality terms), which was created in 1982 an interdisciplinary team of researchers to further our understanding of the complex process of Mexican migration to the United States. The project is a binational research effort co-directed by Jorge Durand, professor of Social Anthropology at the University of Guadalajara (Mexico), and Douglas S. Massey, professor of Sociology and Public Affairs, with a joint appointment in the Woodrow Wilson School, at Princeton University (U.S.).

Since its inception, the MMP's main focus has been to gather social and economic information on Mexican-US migration. The data collected has been compiled in a comprehensive database that is available to the public free of charge for research and educational purposes through its website. The MMP uses the ethnosurvey approach to gather data: in winter months, they randomly sample households in communities throughout Mexico, surveying household heads and members about their trips to the U.S., as well as economic and demographic information. They then conducted the same survey in areas in the U.S., sampling migrants from the same communities they surveyed in Mexico but who have not returned to Mexico. Thus, the sample of migrants includes residents in both Mexico and the U.S.

The MMP170 Database contains an initial file with general demographic, economic, and migratory information for each member of a surveyed household (PERS). Pers170 is a large data which has 132 variables and 176,701 observations. Therefore, we selected 17 relatively meaningful variables and filtered out rows that contain N/A's to create a new dataset labeled `data`.

1.3 Method

We will build a multiple linear regression model to predict household income considering the following variables: `sex`, `relhead`, `age`, `statebrn`, `marstat`, `edyrs`, `occtype`, `usdur1`, `usdurl`, `usdoc1`, `uscity`, `yrborn`. The data dictionary for these variables can be found in project->data->Data Dictionary.

Our response variable is household income. We chose to use the multiple linear regression because our response variable is numerical, and there are multiple predictor variables.

2. Exploratory Data Analysis

2.1 Data Cleaning

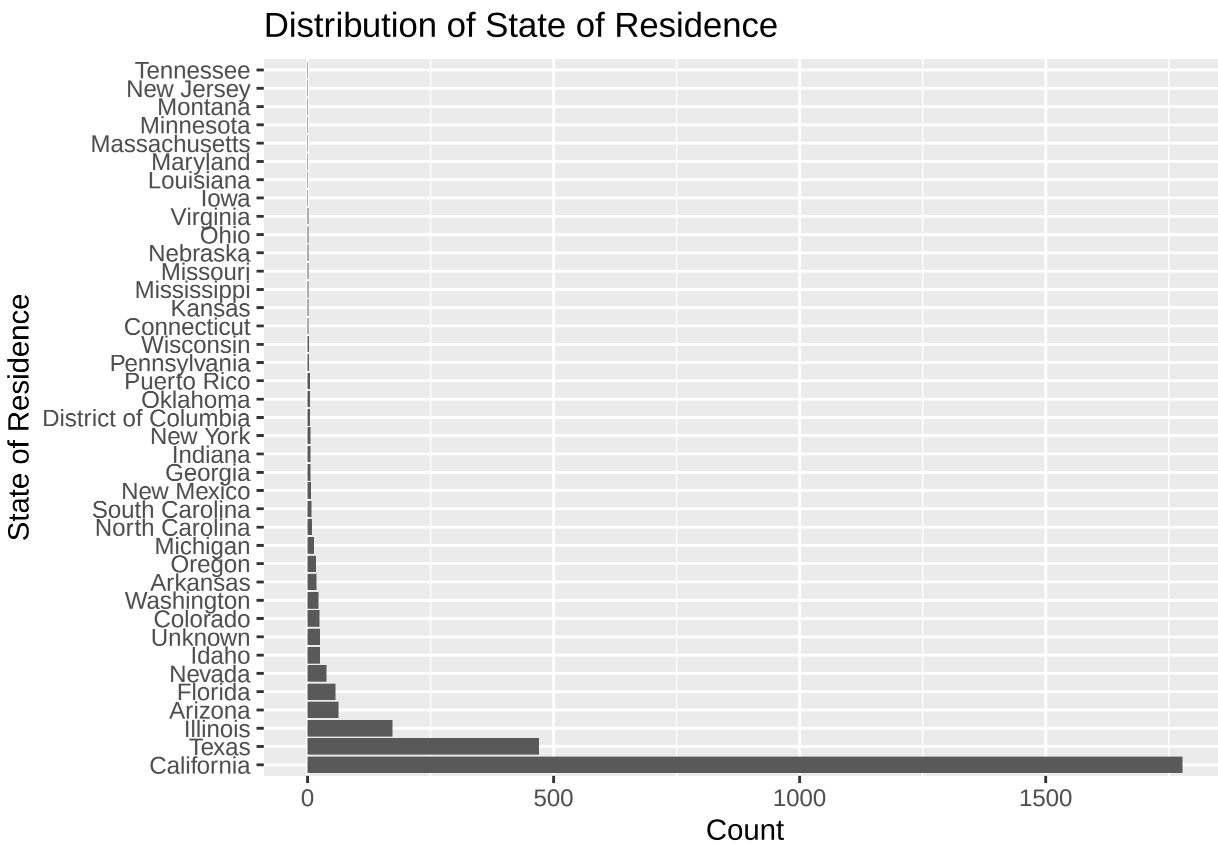
Our original data was extremely complex and necessitated us to clean our data extensively. All of our data cleaning can be found in the proposal.

However, we did make some adjustments according to the feedback Dr. Tackett, which can be found below.

1.4 Updated Data Exploration

1.4.1 Filter Only Immigrants in California

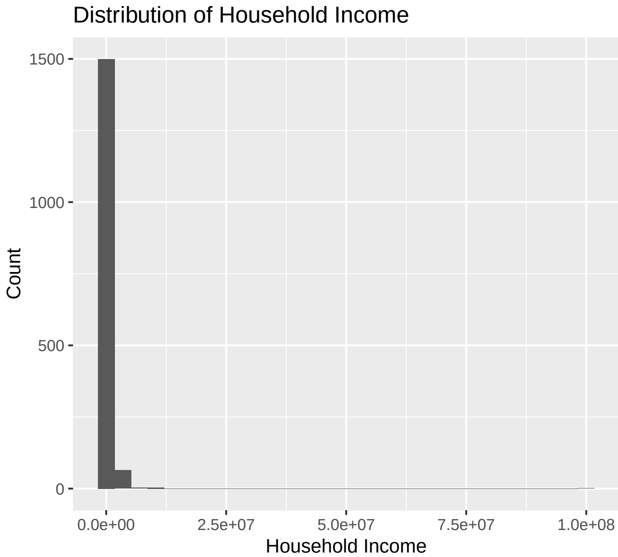
According to our previous data exploration, we found that the overwhelming majority of immigrants settled in California, as shown in the graph below:

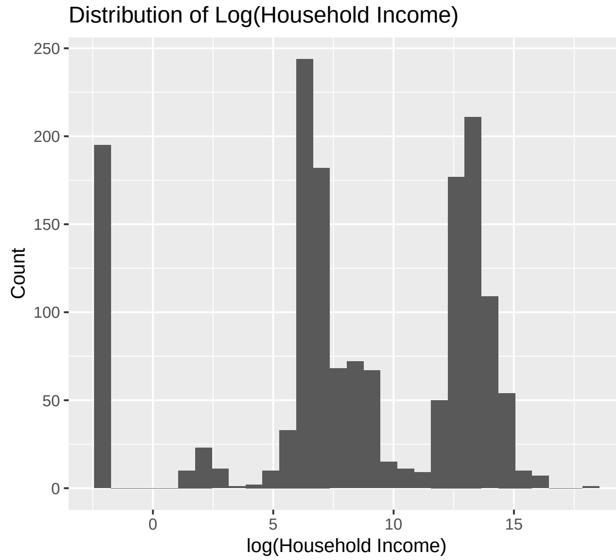


Hence, we decided to concentrate on California alone. Since the originial dataset is large, we have enough data left in California alone to produce meaningful analysis.

1.4.2 Cut Household Income Groups

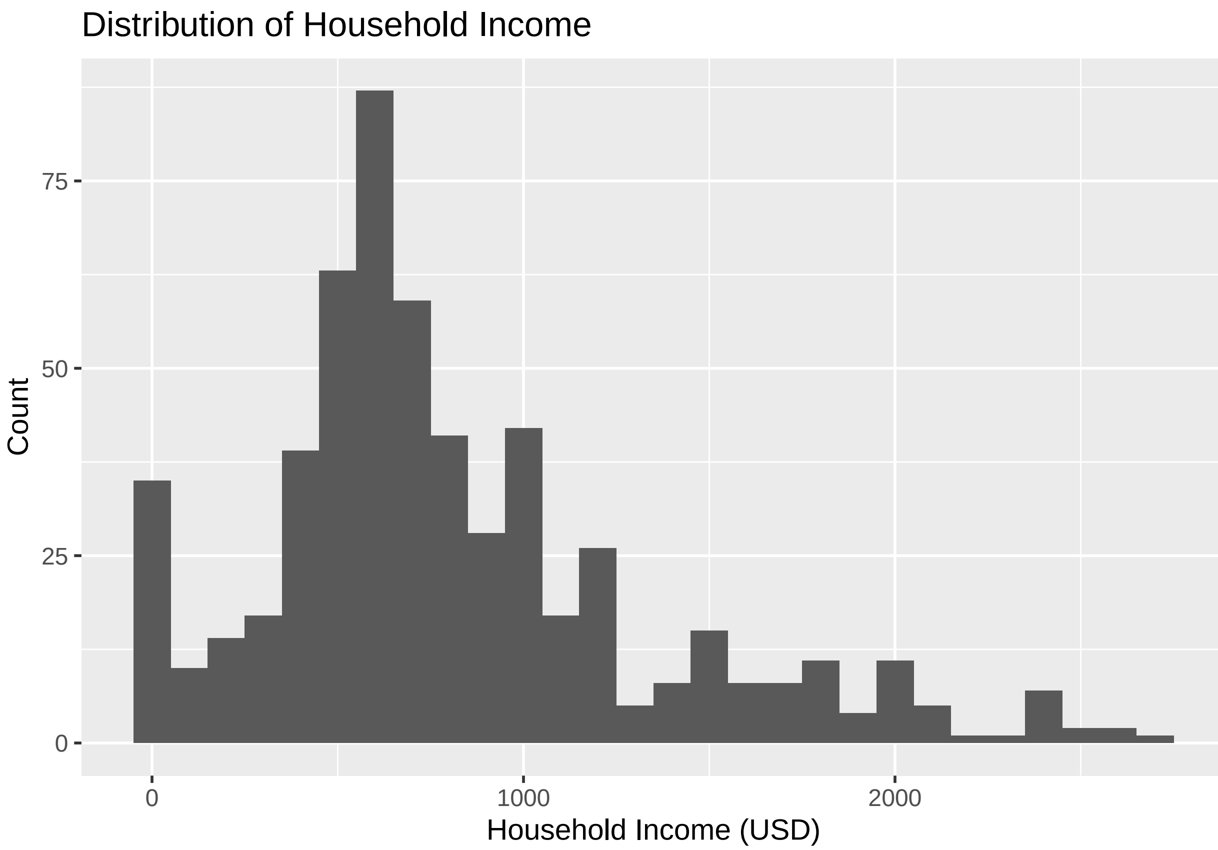
Originally, the distribution of Household Income- our response variable- was bimodal and had a median of 412,647 dollars. A plot of household income in natural units reveals very little information, due to a scattering of very high incomes which blow up the range of the plot. However, a logged plot reveals that household income almost looks like 3 separate distributions:





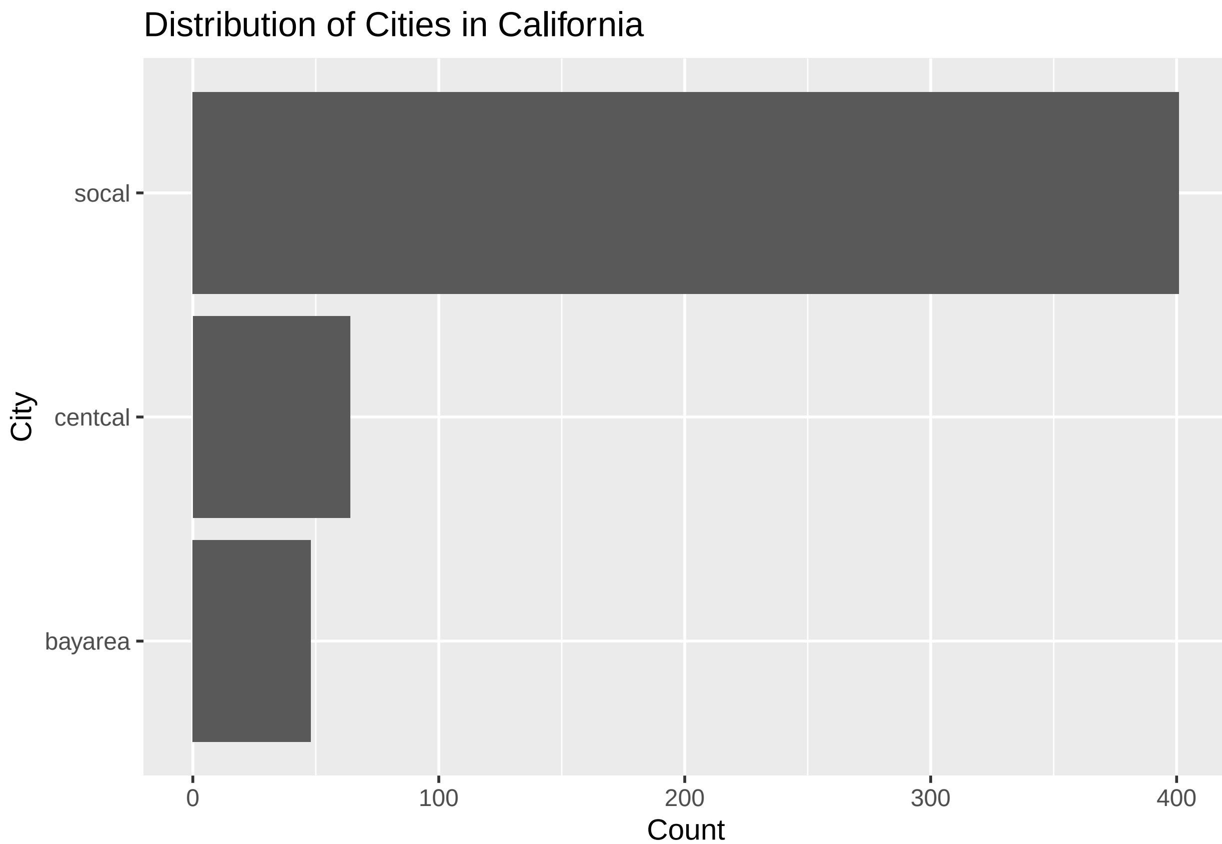
We determined that 412,647 dollars is an absurdly high median income for a survey of largely undocumented immigrants in the US and believe that a significant chunk of the high incomes were actually recorded in pesos. The documentation for the data from the Mexican Migration Project does not specify unit of hhincome; however, the project site details that researchers surveyed communities in Mexico, then traveled to the US to survey communities there. It seems likely that the communities surveyed in Mexico would report income in pesos and those surveyed in the US would report income in USD. However, the data was collected over a period of 10 years, during which the exchange rate between pesos and USD changed significantly. Hence, we cannot simply convert all the incomes that appear to be recorded in pesos into USD.

Therefore, we decided to filter out the incomes above 60,000 to remove what appears to be a second distribution of incomes in pesos. We will also remove incomes of zero from our dataset, because it will interfere with our model accuracy. However, this compromises our model's predictive and explanatory range: our model will only be able to predict or explain the household income of those who already have jobs with income.



Now the distribution of response variable (hhincome) looks like a right skewed normal distribution.

1.4.3 Group cities by region



These immigrants to California arrived to the following cities:

Bay Area: Vallejo-Fairfield-Napa, San Francisco, San Jose, Santa Cruz-Watsonville

Central California: Sacramento, Merced, Fresno, Bakersfield

Southern California: Santa Barbara-Santa Maria-Lompoc, Ventura, Los Angeles-Long Beach, Orange County, Riverside-San Bernardino, and San Diego.

We decided to simplify these cities into 3 regional categories: Bay Area, Southern California and Central California.

Given the comparatively small number of cases in which no city was reported, we deleted these instances. The majority of immigrants went to LA-Long Beach area in Southern California.

1.4.4 Remove Variable "relhead"

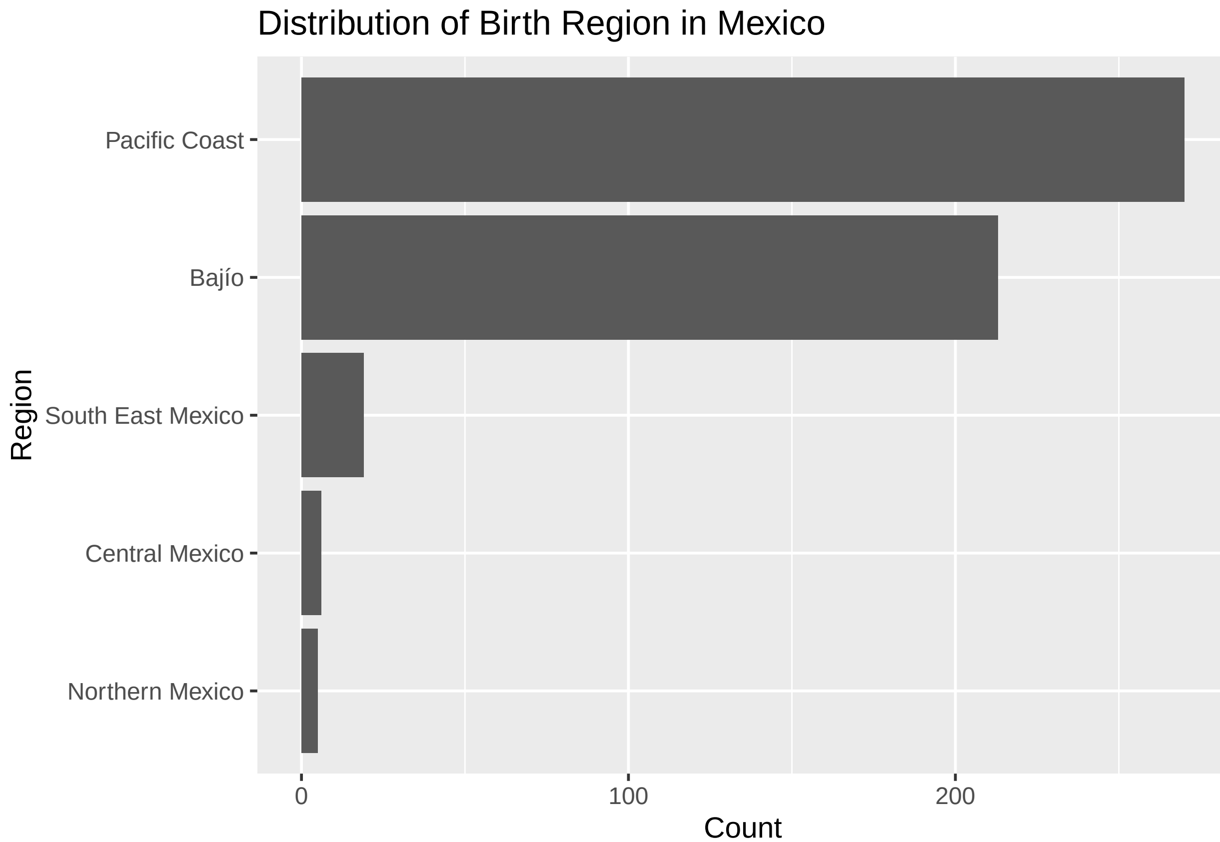
It turned out that all values from relhead (relationship to head of household) in our cleaned data were "1" or head. So we will remove this variable, as well as state variables since we are only using California data. We will also remove place data since we are using uscity, and occ since we are using occtype.

1.4.5 Mean-center "age" , "usdur1" and "usdurl"

We must center age and usdurl in order to have a useful model intercept interpretation.

The mean age in the dataset is 39.43 years ; the mean duration of last US migration is 60.27 months (about 5 years); and the mean duration of first US migration is 43.99 months (less than 3.5 years).

1.4.6 Remove El Salvador Data and regionalize state born variable



We do not have any data from seven states: Baja California Sur, Chiapas, Hidalgo, Quintana Roo, Sinaloa, Tlaxcala, and Yucatán. We had a small amount of non-Mexican data, which we omitted.

We divided the remaining states into the following regions:

South East Mexico: Tabasco, Oaxaca, Campeche, Veracruz

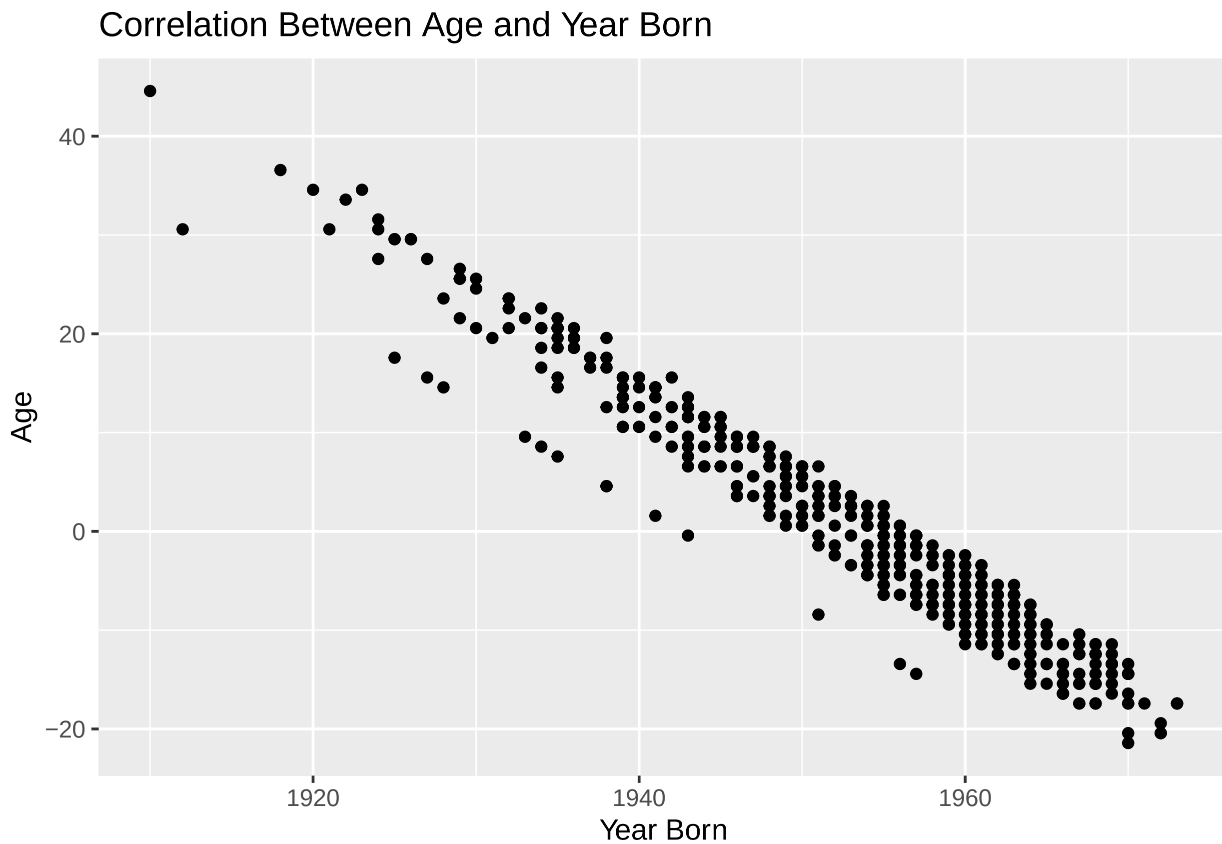
Northern Mexico: Coahuila, Chihuahua, Durango, Nuevo Leon, Sonora, Tamaulipas, Baja California del Norte

Bajío: Aguascalientes, Guanajuato, Querétaro, San Luis Potosí, Zacatecas

Central Mexico: Mexico City, México, Morelos, Puebla

Pacific Coast: Colima, Guerrero, Jalisco, Michoacán, Nayarit

1.4.7 Remove Obvious Collinear Variable



`yrborn` and `age` provide the same information and are perfectly linear, therefore we decided to remove `yrborn` from consideration in the model.

1.4.8 Simplify Occupation Type

We first filter out migrants with occupations indicating lack of paid employment, because our anaylsis focuses only on those migrants

Section 2: Regression Analysis

2. Multiple Linear Regression Model

In an effort to explain which characteristics of migrants influence their household income, we will use a multiple linear regression model. Since our response variable is numerical with mulitple potential predictors, this is the best model at our disposal.

We will consider the potential interaction between principal occupation and number of years of school completed, since those are generally interconnected. We may also consider the interaction between documentation type and occupation type, although the effect may be insignificant. However, if the variables occtype, edyrs, or usdoc1 don't make it through the process of inital model selection, we will not include these interactions in the model as that would not be prudent. If other interactions appear significant, we will include these as well.

We will select our model using AIC criteria, because since we're dealing with people, we want to build a model that accounts for volatile human nature and the ever-changing socioeconomic and political climate that could influence someone's household income. AIC is used when we would rather say a variable is a relevant predictor, when in reality it might not be and so in this case, we would rather err on the side of a false positive because we are dealing with a constantly fluctuating issue.

2.1 Description of Methods

In our first multiple linear regression model, we included all 19 variables. Then, we used backwards model selection to reduce the model to 7 significant variables: edyrs, usdurl, sex, statebrn, usdoc1, occtype and age. We used AIC as the criterion because immigration is a complex social issue, hence we would prefer a model with many predictors and err on the side of false-positive, rather than having a leaner model.

After inital backwards selection, we will explore the possible interactions between remaining variables: edyrs, usdurl, sex, statebrn, usdoc1, occtype and age, to determine if any are significant. The significant interactions that survived to our final model are:

age*edyrs:* $p = 0 < 0.05$
*(This interaction makes sense, because we expect older immigrants to be more educated) statebrn*edyrs: $p = 0.001 < 0.05$ (This interaction makes sense, because we expect different region of Mexico have different level of development and hence access to education.) statebrn*usdurl:* $p = 0.005 < 0.05$ *(This interaction makes sense, because immigrants from certain regions in Mexico may have a easier time staying longer in California because there is already a large community of immigrants from that region there.) age*usdoc1: $p = .007 < 0.05$ (This interaction could make some sense, because the physical stamina required to immigrate illegally could be very related to age, and age is likely considered by the US government in applications for legal immigration status.) usdurl*usdoc1: $p = .012 < 0.05$ (This interaction makes sense, because type of documentation and duration of migration would logically be highly related. Legal immigrants and contract workers can travel back and forth between Mexico and the US with greater ease than undocumented migrants, leading to potentially shorter stays, but they also don't face the same threat of deportation, which could possibly lead them to be able to stay in the US longer)

We included these interactions in our original full model, and did backward selection again to get our final model.

(Please see "Section 5 : Additional Work" for detailed coding process.)

2.2 Full Model after Evaluating Interactions

Model hidden due to length.

2.3 Final model

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	629.277	297.065	2.118	0.035	45.530	1213.024
sexM	327.669	123.480	2.654	0.008	85.025	570.314
age	-22.666	11.074	-2.047	0.041	-44.426	-0.905
statebrnCentral Mexico	2482.855	868.543	2.859	0.004	776.129	4189.581
statebrnNorthern Mexico	-18.793	405.261	-0.046	0.963	-815.149	777.563
statebrnPacific Coast	157.480	95.472	1.649	0.100	-30.127	345.087
statebrnSouth East Mexico	- 185.051	655.663	-0.282	0.778	- 1473.458	1103.356
edyrs	42.483	11.337	3.747	0.000	20.205	64.762
occtypeManufacturing	100.196	62.074	1.614	0.107	-21.783	222.175
occtypeProfessional	208.005	105.018	1.981	0.048	1.641	414.369
occtypeService	138.882	66.983	2.073	0.039	7.258	270.506
usdurl	-1.914	1.340	-1.429	0.154	-4.548	0.719
usdoc1Legal resident	- 244.490	265.390	-0.921	0.357	-765.993	277.013
usdoc1Temporary: Tourist/visitor	- 431.169	275.379	-1.566	0.118	-972.302	109.964

term	estimate	std.error	statistic	p.value	conf.low	conf.high
usdoc1Undocumented	-406.538	253.226	-1.605	0.109	-904.139	91.064
age:edyrs	2.434	0.620	3.924	0.000	1.215	3.654
statebrnCentral Mexico:edyrs	-304.707	114.163	-2.669	0.008	-529.042	-80.372
statebrnNorthern Mexico:edyrs	14.954	44.830	0.334	0.739	-73.138	103.047
statebrnPacific Coast:edyrs	-38.703	13.223	-2.927	0.004	-64.688	-12.719
statebrnSouth East Mexico:edyrs	10.996	35.425	0.310	0.756	-58.616	80.608
statebrnCentral Mexico:usdurl	10.870	6.326	1.718	0.086	-1.562	23.301
statebrnNorthern Mexico:usdurl	-5.348	1.852	-2.888	0.004	-8.987	-1.709
statebrnPacific Coast:usdurl	-0.856	0.587	-1.460	0.145	-2.009	0.296
statebrnSouth East Mexico:usdurl	-5.475	11.303	-0.484	0.628	-27.686	16.736
age:usdoc1Legal resident	-1.828	14.365	-0.127	0.899	-30.056	26.400
age:usdoc1Temporary: Tourist/visitor	16.945	15.000	1.130	0.259	-12.530	46.419
age:usdoc1Undocumented	17.680	11.604	1.524	0.128	-5.123	40.483
usdurl:usdoc1Legal resident	2.272	1.453	1.564	0.119	-0.583	5.127
usdurl:usdoc1Temporary: Tourist/visitor	1.920	1.498	1.282	0.201	-1.024	4.864
usdurl:usdoc1Undocumented	3.345	1.302	2.570	0.010	0.787	5.902

2.4 Description of Method in Model Diagnostics

We checked leverage, standardized residuals, estimate of standard deviation, Cook's distance, VIF and adjusted R-squared. (Please see "Section 5 : Additional Work" for detailed codes and graphs)

2.4.1 Leverage

Just under half of our observations are high leverage points, meaning that their combinations of values for the predictor variables are very far from the typical combinations in the data. Because human circumstances and economic conditions are often so extremely variable, we would not expect most migrants to share common values for the predictor variables.

Of the individuals in the data with high leverage, two are highly educated professionals, and three have 5 years of education and work in manufacturing jobs. All are male. Age, documentation, and duration of migration vary. These points are potentially, but not certainly, influential points, so we use other methods to sort out influential points.

2.4.2 Standardized Residuals

The 6% of our observations with standardized residuals of magnitude greater than 2 should be examined more closely- these are outliers, but they may not have an impact on the regression line. We can look plots of the standardized residuals versus all of our predictors. Plots of the standardized residuals for each predictor variable reveal that, for the most part, our data satisfies the constant variance assumption.

2.4.3 Estimate of Standard Deviation

The estimate of our regression standard deviation using all observations is 481.0428, whereas the standard deviation estimate without points with large magnitude standardized residuals is 370.9477. Removing points with large magnitude standardized residuals would affect our conclusions by decreasing the standard error associated with our model coefficients, however, we do not want to damage our model's integrity and explanatory power by removing too much human variability from the observations we base it on. We will examine Cook's Distance to see if any observations have excessive overall impact or significantly affect the estimated coefficients when removed.

2.4.4 Cook's Distance

No observations have a Cook's Distance greater than 1, thus none of the high leverage points exert significantly greater influence on the final coefficients of our model than the other points and could distort our explanations.

2.4.5 VIF

There are 10 coefficients with high VIFs (>10):

usdoc1Legal resident: 10.424955 usdurl:usdoc1Undocumented: 18.919794 statebrnCentral Mexico: 19.324207 statebrnCentral Mexico:edyrs: 19.878084 usdoc1Undocumented: 20.608986 statebrnSouth East Mexico:usdurl: 24.55331 age:usdoc1Undocumented: 25.065321 usdurl: 28.95936 statebrnSouth East Mexico: 33.951032 age: 34.366655

It is likely the state born coefficients are collinear with education, as education is highly related to region in Mexico – Central Mexico and Northern Mexico have the best schools, while the South East has the worst. Length of time in the US obviously will be correlated to age, as well. Additionally, the coefficients of the regions may have high collinearity because when we divided the birth state into regions, there are very few and very geographically sparse observations in the South East Mexico, and a lot more observations in Central Mexico. Hence, in order to make each region more representative, we included some of the ambiguous states that could possibly be included in both regions into South East Mexico. Since the geographical regional divide is subjective and continuous, we expect there to be collinearity.

The duration of time in the US is likely collinear with documentation status, as the longer a person lives in the US, the harder it is to be undocumented.

2.4.6 Adjusted R-squared

The adjusted R-squared of our final model is 0.1810094, meaning that our model explains around 18.1% of the variation in household income. This is a small percentage. However, given that there are numerous social determinants of income, and we only included Californian data and those who have income between 1 and 60,000, the R-squared seems reasonable.

Section 3: Discussion and Limitations

3.1 Limitations

In order to complete an effective analysis in the time given, we greatly simplified our raw data to predict our response variable, household income. We ended up only analyzing a subgroup of the immigrants and focused on those who migrated to California because they made up a large majority of our original dataset. However, because of that, our findings may not be able to be generalized into other states in the US. If we were given more time, we would have analyzed the entirety of the dataset.

Additionally, we cut a chunk of the data out because it appeared that some of the income was reported in pesos and USD, though we are not definitively sure. Further analysis could investigate why it appeared that some income was reported in a potentially different currency and adjust for it so we can include all observations in our analysis. We also cut off the data with no income to avoid the influence of zero inflation on the final model, hence biasing the model against immigrants who are unemployed. Future models should be adjusted for zero inflation.

Moreover, in an attempt to simplify the variable "statebrn", we grouped observations into regions. However, in order to arrive at a balanced grouping in terms of the number of observations in each region, we artificially divided the regions geographically, rather than dividing them according to socio-economic characteristics. As a result, the household income in some regions, such as South East Mexico, has a wide range. Furthermore, through compromising between geographic integrity and number of observations in each region, the majority of observations are still in Pacific Coast and Bajío regions due to the nature of the data. In fact, only those 2 regions had over 30 observations. Further work can look into weighing mechanisms for multiple linear models.

We also had very few data points for female immigrants. In the future we would want more equal numbers.

According to our analysis of leverage and adjusted R-square, we conclude that there might be many outliers in our data, which makes sense since the immigrants in the data have drastically different demographics and income. Hence, our model should only be taken as a reference to analyse general trends, rather than to predict precise incomes. Given that wage depends on numerous socio-economic factors, our model is satisfactory, yet it cannot tell the entire story.

If we could continue to work on the project, we would operate under the assumption that the household income that is unusual was reported in pesos and potentially recorded in the Mexico and split the data set into two and investigate that. Our model could be stronger if we were able to include this very valuable data and inform our predictions with this information.

3.2 Prediction

3.2.1 Effect of "Gender" on Wage

```
##        fit      lwr      upr
## 1 905.5048 814.7695 996.2402
```

For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", his predicted wage is $905.59. We are 95% confident that the actual salary falls in the interval of [814.77, 996.24].

```
##        fit      lwr      upr
## 1 577.8354 320.7065 834.9644
```

For a female who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", her predicted salary is $577.84. We are 95% confident that the actual salary falls in the interval of [320.71, 834.96].

We can see from the prediction that there is a large gender wage gap, since a male's predicted wage is much higher than a female of the same average demographics.

3.2.2 Effect of "State born" on Wage

We used male as a model input because the majority of the immigrants in our data set are male. We used edyrs = 6 as the input because it is the average number of years of education for the data set. Manufacturing is the most common occupation type in the data, undocumented the most common immigration status. The rest of the inputs are 0 since those predictors are mean-centered.

```
##        fit      lwr      upr
## 1 905.5048 814.7695 996.2402
```

For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", his predicted wage is $905.50 We are 95% confident that the actual salary falls in the interval of [814.77, 996.24].

```
##        fit     lwr      upr
## 1 1560.119 1054.74 2065.498
```

For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of of "Central Mexico", his predicted salary is $1560.12 We are 95% confident that the actual salary falls in the interval of [1054.74, 2065.50].

```
##        fit      lwr      upr
## 1 976.4381 502.3831 1450.493
```

For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of of "Northern Mexico", his predicted salary is $976.44 We are 95% confident that the actual salary falls in the interval of [502.38, 1450.50].

```
##        fit       lwr      upr
## 1 786.4308 -317.2469 1890.109
```

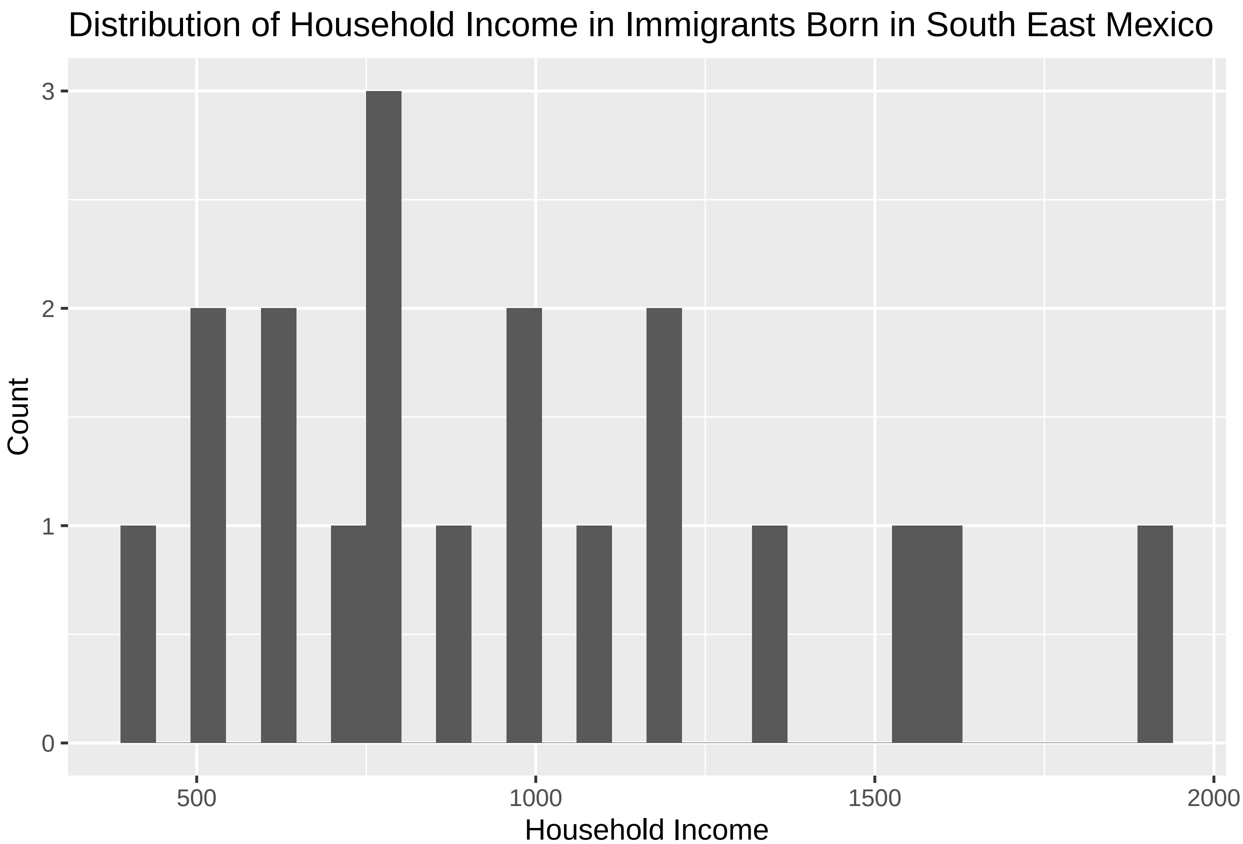
For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of of "South East Mexico", his predicted salary is $786.43 We are 95% confident that the actual salary falls in the interval of [-317.25, 1890.11].

```
##        fit     lwr      upr
## 1 830.7653 743.669 917.8617
```

For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), works in manufacturing (most common occupation in the dataset), has undocumented status (most common documentation in the dataset), and was born in the region of of "Pacific Coast", his predicted salary is $830.77 We are 95% confident that the actual salary falls in the interval of [743.67, 917.86].

The prediction suggest a hierarchy in wage discrimination based on the regions in Mexico that the immigrants are born in. Immigrants from the region of Central Mexico has the highest predicted wage, followed by Northern Mexico, Bajío, Pacific Coast, and South East Mexico has the lowest average predicted wage. This is supported by literature on economic inequality in Mexico. Specifically, early industrialization started in Central and Northern Mexico, allowing more mobility and opportunity for education and trade in these regions. In fact, in 2012, the northern border states (6 of the 32) accounted for 52.87% of the total export value. Therefore, it is possible that as a result, immigrants from these regions have an easier time earning relative higher wages than those from other regions.

However, it is worth noting that the confidence interval of South East Mexico is very large, including as low as 0 and as high as $1901.58. This could be due to the small sample size, as shown in the histogram below:




```
## [1] 19
```

There are only actually 19 observations in the data from this region.

It may also be because this region was artifiically created from 4 distinct cultural/economic/geographic regions in Mexico: the Yucatan Peninsula, Oaxaca, Veracruz and Chiapas & Tabasco. The regions were combined in order to be useful for analysis, but with more data we would have prefered to keep them as seperate regions, especially since Veracruz is relatively better-off than the rest of the states.

3.2.3 Effect of "Occupation Type" on Wage

We used male as a model input because the majority of the immigrants in our data set are male. We used edyrs = 6 as the input because it is the average number of years of education for the data set. Undocumented is the most common immigration status and many of the immigrants in the data set were born in the region of Bajío. The rest of the inputs are 0 since those predictors are mean-centered.

```
##        fit      lwr      upr
## 1 905.5048 814.7695 996.2402
```

For a male who is 39 years old (average age), has 6 years of education (average edyrs), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", his predicted wage is $905.50 We are 95% confident that the actual salary falls in the interval of [814.7695, 996.2402].

```
##        fit      lwr      upr
## 1 805.3087 695.6034 915.0141
```

For a male who is 39 years old (average age), has 4.6 years of education (average edyrs for Agriculture workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", his predicted wage is $805.31. We are 95% confident that the actual salary falls in the interval of [695.6034, 915.0141].

```
##        fit      lwr      upr
## 1 905.5048 814.7695 996.2402
```

For a male who is 39 years old (average age), has 7.25 years of education (average edyrs for Service industry workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", his predicted wage is $905.50. We are 95% confident that the actual salary falls in the interval of [814.7695, 996.2402].

```
##        fit      lwr      upr
## 1 1013.314 826.5249 1200.102
```

For a male who is 39 years old (average age), has 9.972 years of education (average edyrs for Professional workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío", his predicted wage is $1013.31 We are 95% confident that the actual salary falls in the interval of [826.5249, 1200.102].

```
##      edyrs
##  Min.   : 0.0
##  1st Qu.: 2.0
##  Median : 4.0
##  Mean   : 4.6
##  3rd Qu.: 6.0
##  Max.   :13.0
```

```
##      edyrs
##  Min.   : 0.000
##  1st Qu.: 4.000
##  Median : 6.000
##  Mean   : 6.281
##  3rd Qu.: 9.000
##  Max.   :17.000
```

```
##      edyrs
##  Min.   : 0.00
##  1st Qu.: 4.00
##  Median : 6.00
##  Mean   : 7.25
##  3rd Qu.: 9.00
##  Max.   :17.00
```

```
##      edyrs
##  Min.   : 1.000
##  1st Qu.: 7.000
##  Median : 9.000
##  Mean   : 9.972
##  3rd Qu.:13.000
##  Max.   :16.000
```

We used the same level of education for each prediction in order to focus on the effect of occupation type. However, different occupations tend to require different levels of education- for agriculture, manufacturing, service, and professional occupations the mean years spent in education are 4.6, 6.281, 7.25, and 9.972 respectively. Using the same education level for each of these predictions may not be representative of what is likely to occur in the real world; however, it allows us to examine the isolated effect of occupation type on household income.

3.2.4 Effect of "Documentation Type" on Wage

```
##        fit      lwr      upr
## 1 917.4427 826.3196 1008.566
```

For a male who is 39 years old (average age), has 6.281 years of education (average edyrs for Manufacturing workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has undocumented status (most common documentation in the dataset), and was born in the region of "Bajío" (Baseline region), his predicted wage is $917.44 We are 95% confident that the actual salary falls in the interval of [826.32, 1008.57].

```
##        fit     lwr      upr
## 1 892.8114 661.567 1124.056
```

For a male who is 39 years old (average age), has 6.281 years of education (average edyrs for Manufacturing workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has "Temporary: Tourist/visitor" status, and was born in the region of "Bajío" (Baseline region), his predicted wage is $892.81 We are 95% confident that the actual salary falls in the interval of [661.57, 1124.06].

```
##       fit      lwr      upr
## 1 1323.98 818.7793 1829.182
```

For a male who is 39 years old (average age), has 6.281 years of education (average edyrs for Manufacturing workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has "Contract - Bracero" status, and was born in the region of "Bajío" (Baseline region), his predicted wage is $1323.98 We are 95% confident that the actual salary falls in the interval of [818.78, 1829.18].

```
##       fit    lwr     upr
## 1 1079.49 897.65 1261.33
```

For a male who is 39 years old (average age), has 6.281 years of education (average edyrs for Manufacturing workers), first immigrated to the US for 5 years (average duration), last immigrated to the US for 3 years and 7 months (average duration), has "Legal resident" status, and was born in the region of "Bajío" (Baseline region), his predicted wage is $1079.49 We are 95% confident that the actual salary falls in the interval of [897.65, 1261.33].

The prediction suggest a hierarchy in wage discrimination based on the immigrants' documentation type. Immigrants who have "contract - barcero" documentation earn the highest predicted household income, followed by legal residents, undocumented, and lastly temporary workers. This is counter intuitive because one would imagine legal residents to earn more. However, this could be due to the relative imbalance in the observations in the two groups: the number of observations in "Legal resident" is significantly fewer than that in "Contract - Barcero".

Section 4: Conclusion

Through our exploration and analysis, we found sex, age, years of education, occupation type, documentation type, duration of last US immigration and region born to be significant predictors of household income of Mexican immigrant living in California. Among these, there are significant interactions between: - age and years of education, - age and documentation type, - documentation type and duration of last US migration, - region born and years of education, - and region born and duration of last US migration.

From our predictions, we observe a large gender wage gap: the average male has predicted wage of 893.32 USD, whereas the average female has predicted wage of 590.11 USD. It is shocking that the average wage for males in this sample is almost two times that of females in this sample. However, we also had significantly more male data points in this dataset, with 21 female datapoints and 477 male datapoints.

We also observed regional differences in terms of where the immigrant was born. Immigrants from the region of Central Mexico have the highest predicted wage, followed by Northern Mexico, Bajío, Pacific Coast, and South East Mexico has the lowest average predicted wage. However, since there is a prominent imbalance in number of observations from various regions, this conclusion should be taken with caution – for example, we are notably missing data from two of the three states in the Yucatan Peninsula in the South East of Mexico, and over 50% of our data points are from the Pacific Coast.

In terms of occupation type, as expected the highest incomes are found among professionals, with service and manufacturing workers close behind. As anticipated, agricultural workers had the lowest income. In this case, our data is robust, as each category has over 30 datapoints.

In terms of documentation type, we observed a hierarchy in wage discrimination based on the immigrants' documentation type. Immigrants who have "contract - barcero" documentation earn the highest predicted household income, followed by legal residents, undocumented, and lastly temporary workers.

Section 5: Additional Work

5.1 Full Initial Model, No Interactions

term	estimate	std.error	statistic	p.value
(Intercept)	336.219	260.490	1.291	0.197
sexM	306.283	183.313	1.671	0.095
age	6.422	2.789	2.302	

0.022

statebrnCentral Mexico

243.019

217.955

1.115

0.265

statebrnNorthern Mexico

-84.806

235.097

-0.361

0.718

statebrnPacific Coast

-91.483

49.246

-1.858

0.064

statebrnSouth East Mexico

112.737

125.783

0.896

0.371

marstatDivorced

233.605

215.615

1.083

0.279

marstatMarried

34.821

116.576

0.299

0.765

marstatNever married

-165.591

162.346

-1.020

0.308

marstatSeparated

74.747

229.565

0.326

0.745

marstatWidowed

95.702

242.640

0.394

0.693

edyrs

15.296

7.580

2.018

0.044

occtypeManufacturing

118.000

64.682

1.824

0.069

occtypeProfessional

258.447

108.580

2.380

0.018

occtypeService

149.976

70.720

2.121

0.034

usdur1

-0.375

0.453

-0.828

0.408

usdurl

0.856

0.388

2.207

0.028

usdoc1Legal resident

161.966

145.344

1.114

0.266

usdoc1Temporary: Tourist/visitor

-144.299

155.965

-0.925

0.355

usdoc1Undocumented

-47.150

121.970

-0.387

0.699

uscitycentcal

39.085

102.900

0.380

0.704

uscitysocal

40.916

82.303

0.497

0.619

5.2 Backward selection

```
## Start:  AIC=6233.96
## hhincome ~ sex + age + statebrn + marstat + edyrs + occtype +
##     usdur1 + usdurl + usdoc1 + uscity
##
##            Df Sum of Sq       RSS    AIC
## - marstat   5   1117380 125170807 6228.4
## - uscity    2     64974 124118402 6230.2
```

```
## - usdur1    1    178991 124232419 6232.7
## - statebrn  4   1815643 125869071 6233.2
## <none>                  124053428 6234.0
## - usdoc1    3   1706651 125760078 6234.8
## - sex       1    729080 124782508 6234.9
## - occtype   3   1862901 125916329 6235.4
## - edyrs     1   1063307 125116735 6236.2
## - usdurl    1   1271734 125325161 6237.0
## - age       1   1384513 125437941 6237.5
##
## Step:  AIC=6228.43
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1 + uscity
##
##            Df Sum of Sq       RSS    AIC
## - uscity    2     75805 125246612 6224.7
## - usdur1    1    214264 125385071 6227.3
## <none>                  125170807 6228.4
## - usdoc1    3   1729934 126900742 6229.3
## - occtype   3   1755477 126926284 6229.4
## - statebrn  4   2273850 127444657 6229.4
## - edyrs     1   1108665 126279473 6230.8
## - sex       1   1162270 126333077 6231.0
## - usdurl    1   1342243 126513050 6231.7
## - age       1   1857888 127028695 6233.8
##
## Step:  AIC=6224.73
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1
##
##            Df Sum of Sq       RSS    AIC
## - usdur1    1    188932 125435544 6223.5
## <none>                  125246612 6224.7
## - usdoc1    3   1666878 126913490 6225.3
## - statebrn  4   2314226 127560838 6225.8
## - occtype   3   1814497 127061109 6225.9
## - edyrs     1   1094602 126341214 6227.1
## - sex       1   1156574 126403186 6227.3
## - usdurl    1   1311263 126557875 6227.9
## - age       1   1846482 127093094 6230.0
##
## Step:  AIC=6223.48
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdurl +
##     usdoc1
##
##            Df Sum of Sq       RSS    AIC
## <none>                  125435544 6223.5
## - usdoc1    3   1631114 127066657 6223.9
## - occtype   3   1796091 127231634 6224.6
## - statebrn  4   2353643 127789187 6224.7
## - edyrs     1   1146434 126581977 6226.0
## - sex       1   1309985 126745529 6226.7
## - usdurl    1   1324851 126760395 6226.7
## - age       1   1959638 127395182 6229.2
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	426.973	187.806	2.273	0.023	57.956	795.990
sexM	277.772	123.678	2.246	0.025	34.759	520.785
age	7.381	2.687	2.747	0.006	2.101	12.660
statebrnCentral Mexico	286.819	215.560	1.331	0.184	-136.733	710.371
statebrnNorthern Mexico	-105.700	233.279	-0.453	0.651	-564.066	352.667
statebrnPacific Coast	-103.875	48.530	-2.140	0.033	-199.231	-8.519
statebrnSouth East Mexico	108.414	125.040	0.867	0.386	-137.277	354.104
edyrs	15.712	7.478	2.101	0.036	1.018	30.406
occtypeManufacturing	120.484	63.986	1.883	0.060	-5.241	246.208
occtypeProfessional	253.715	107.237	2.366	0.018	43.007	464.424
occtypeService	138.278	69.463	1.991	0.047	1.790	274.766
usdurl	0.646	0.286	2.259	0.024	0.084	1.207
usdoc1Legal resident	176.353	144.014	1.225	0.221	-106.619	459.324
usdoc1Temporary: Tourist/visitor	-90.471	150.968	-0.599	0.549	-387.106	206.163
usdoc1Undocumented	-38.190	120.305	-0.317	0.751	-274.576	198.197

Using backward selection based on AIC, we narrowed down to 7 variables: sex, edyrs, usdurl, statebrn, occtype, usdoc1 and age.

5.3 Interactions

To find potential interactions between the 7 variables, we used nested-F test for each of the possible interactions:

After inital backwards selection, we will explore the possible interactions between remaining variables: `edyrs`, `usdurl`, `sex`, `statebrn`, `occtype`, `usdoc1` and `age`, to determine if any are significant.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
482	125424763	1	10780.7	0.839

First, we tested the interaction between `edyrs` and `usdurl`. The p-value for this test was $0.839 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
482	124081486	1	1354058	0.022

Then, we tested the interaction between `sex` and `usdurl`. The p-value for this test was $0.022 < 0.05$, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
482	124099986	1	1335557	0.023

Then, we tested the interaction between `age` and `usdurl`. The p-value for this test was $0.023 < 0.05$, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
482	125320504	1	115039.9	0.506

Then, we tested the interaction between `sex` and `edyrs`. The p-value for this test was $0.506 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
482	119981867	1	5453677	0

Then, we tested the interaction between `age` and `edyrs`. The p-value for this test was $0 < 0.05$, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
482	125120075	1	315468.6	0.27

Then, we tested the interaction between `age` and `sex`. The p-value for this test was $0.27 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	124722391	3	713153	0.433

Then, we tested the interaction between `statebrn` and `sex`. The p-value for this test was $0.433 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
479	123417127	4	2018417	0.098

Then, we tested the interaction between `statebrn` and `age`. The p-value for this test was $0.098 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
479	120606332	4	4829212	0.001

Then, we tested the interaction between `statebrn` and `edyrs`. The p-value for this test was $0.001 < 0.05$, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
479	121672866	4	3762678	0.005

Then, we tested the interaction between `statebrn` and `usdurl`. The p-value for this test was 0.005 $<$ 0.05, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	125072371	3	363172.5	0.707

Then, we tested the interaction between `occtype` and `sex`. The p-value for this test was 0.707 $>$ 0.05, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	124082703	3	1352841	0.155

Then, we tested the interaction between `occtype` and `age`. The p-value for this test was 0.155 $>$ 0.05, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
474	120267831	9	5167712	0.016

Then, we tested the interaction between `occtype` and `statebrn`. The p-value for this test was 0.016 $<$ 0.05, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	124859480	3	576063.6	0.529

Then, we tested the interaction between `occtype` and `edyrs`. The p-value for this test was 0.529 $>$ 0.05, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	123994932	3	1440612	0.134

Then, we tested the interaction between `occtype` and `usdurl`. The p-value for this test was 0.134 $>$ 0.05, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
481	125108642	2	326901.9	0.533

Then, we tested the interaction between `usdoc1` and `sex`. The p-value for this test was 0.533 $>$ 0.05, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	122360867	3	3074676	0.007

Then, we tested the interaction between `usdoc1` and `age`. The p-value for this test was $0.007 < 0.05$, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
476	121325821	7	4109723	0.024

Then, we tested the interaction between `usdoc1` and `statebrn`. The p-value for this test was $0.024 < 0.05$, therefore we will include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	123759147	3	1676397	0.09

Then, we tested the interaction between `usdoc1` and `edyrs`. The p-value for this test was $0.09 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
481	125108642	2	326901.9	0.533

Then, we tested the interaction between `usdoc1` and `occtype`. The p-value for this test was $0.53 > 0.05$, therefore we will not include it in the model.

Res.Df	RSS	Df	Sum of Sq	Pr(>Chi)
483	125435544	NA	NA	NA
480	122649587	3	2785957	0.012

Then, we tested the interaction between `usdoc1` and `usdurl`. The p-value for this test was $0.012 < 0.05$, therefore we will include it in the model.

Through nested F-test, we observed significant interactions between sex & usdurl, age & usdurl, age * edyrs, statebrn & edyrs, statebrn & usdurl, occtype & statebrn, usdoc1 & age, usdoc1 & statebrn, and usdoc1 & usdurl, and we will be including them in our model selection.

5.4 Model with Interactions

term

estimate

std.error

statistic

p.value

(Intercept)

217.692

396.745

0.549

0.583

sexM

348.484

130.134

2.678

0.008

age

-11.892

12.916

-0.921

0.358

edyrs

33.262

11.893

2.797

0.005

usdurl

-2.256

1.936

-1.165

0.245

usdoc1Legal resident

269.145

399.689

0.673

0.501

usdoc1Temporary: Tourist/visitor

125.547

415.176

0.302

0.762

usdoc1Undocumented

-88.618

374.066

-0.237

0.813

occtypeManufacturing

274.716

91.986

2.987

0.003

occtypeProfessional

372.524

168.890

2.206

0.028

occtypeService

232.285

95.798

2.425

0.016

statebrnCentral Mexico

5231.495

5100.564

1.026

0.306

statebrnNorthern Mexico

-593916.558

366494.740

-1.621

0.106

statebrnPacific Coast

475.250

243.417

1.952

0.052

statebrnSouth East Mexico

-646.675

894.884

-0.723

0.470

sexM:usdurl

-0.867

0.952

-0.911

0.363

age:usdurl

0.026

0.024

1.069

0.286

age:edyrs

2.473

0.633

3.904

0.000

edyrs:statebrnCentral Mexico

-614.591

582.353

-1.055

0.292

edyrs:statebrnNorthern Mexico

87520.240

53969.780

1.622

0.106

edyrs:statebrnPacific Coast

-25.925

14.171

-1.829

0.068

edyrs:statebrnSouth East Mexico

53.522

55.816

0.959

0.338

usdurl:statebrnCentral Mexico

11.619

6.295

1.846

0.066

usdurl:statebrnNorthern Mexico

545.695

339.437

1.608

0.109

usdurl:statebrnPacific Coast

-0.154

0.650

-0.237

0.813

usdurl:statebrnSouth East Mexico

-7.666

12.508

-0.613

0.540

occtypeManufacturing:statebrnCentral Mexico

-1308.260

2225.761

-0.588

0.557

occtypeManufacturing:statebrnNorthern Mexico

362198.763

223688.926

1.619

0.106

occtypeProfessional:statebrnNorthern Mexico

-779682.927

480632.930

-1.622

0.105

occtypeManufacturing:statebrnPacific Coast

-318.634

124.474

-2.560

0.011

occtypeProfessional:statebrnPacific Coast

-270.848

221.416

-1.223

0.222

occtypeService:statebrnPacific Coast

-197.902

133.179

-1.486

0.138

occtypeManufacturing:statebrnSouth East Mexico

-60.910

358.390

-0.170

0.865

occtypeProfessional:statebrnSouth East Mexico

-573.141

511.381

-1.121

0.263

occtypeService:statebrnSouth East Mexico

-315.750

417.685

-0.756

0.450

age:usdoc1Legal resident

-11.582

16.043

-0.722

0.471

age:usdoc1Temporary: Tourist/visitor

3.106

16.639

0.187

0.852

age:usdoc1Undocumented

6.251

13.507

0.463

0.644

usdoc1Legal resident:statebrnPacific Coast

-538.944

305.471

-1.764

0.078

usdoc1Temporary: Tourist/visitor:statebrnPacific Coast

-464.635

320.220

-1.451

0.147

usdoc1Undocumented:statebrnPacific Coast

-153.594

246.733

-0.623

0.534

usdoc1Temporary: Tourist/visitor:statebrnSouth East Mexico

-95.652

881.469

-0.109

0.914

usdoc1Undocumented:statebrnSouth East Mexico

307.364

578.957

0.531

0.596

usdurl:usdoc1Legal resident

2.775

1.592

1.744

0.082

usdurl:usdoc1Temporary: Tourist/visitor

2.355

1.607

1.465

0.144

usdurl:usdoc1Undocumented

3.868

1.407

2.749

0.006

5.5 Backwards Selection from Initial Model with Interactions

Since we observed 9 pairs of significant interactions, we will do the backward selection again with the new interaction terms.

term

estimate

std.error

statistic

p.value

(Intercept)

197.187

435.069

0.453

0.651

sexM

332.595

184.534

1.802

0.072

age

-11.771

12.992

-0.906

0.365

statebrnCentral Mexico

5894.923

5152.957

1.144

0.253

statebrnNorthern Mexico

-592226.584

370577.697

-1.598

0.111

statebrnPacific Coast

466.876

247.627

1.885

0.060

statebrnSouth East Mexico

-737.453

905.264

-0.815

0.416

marstatDivorced

77.826

211.837

0.367

0.714

marstatMarried

22.708

110.966

0.205

0.838

marstatNever married

-169.691

154.579

-1.098

0.273

marstatSeparated

90.457

220.463

0.410

0.682

marstatWidowed

-65.660

240.294

-0.273

0.785

edyrs

32.068

12.105

2.649

0.008

occtypeManufacturing

271.574

92.466

2.937

0.003

occtypeProfessional

376.031

170.446

2.206

0.028

occtypeService

245.302

97.644

2.512

0.012

usdur1

-0.446

0.467

-0.957

0.339

usdurl

-1.812

2.030

-0.893

0.373

usdoc1Legal resident

268.441

402.865

0.666

0.506

usdoc1Temporary: Tourist/visitor

129.304

419.976

0.308

0.758

usdoc1Undocumented

-75.168

377.149

-0.199

0.842

uscitycentcal

20.593

98.879

0.208

0.835

uscitysocal

3.642

81.210

0.045

0.964

sexM:usdurl

-1.239

1.023

-1.212

0.226

age:usdurl

0.024

0.025

0.990

0.323

age:edyrs

2.350

0.645

3.644

0.000

statebrnCentral Mexico:edyrs

-695.492

588.878

-1.181

0.238

statebrnNorthern Mexico:edyrs

87272.462

54570.923

1.599

0.110

statebrnPacific Coast:edyrs

-24.596

14.350

-1.714

0.087

statebrnSouth East Mexico:edyrs

58.283

56.289

1.035

0.301

statebrnCentral Mexico:usdurl

11.188

6.352

1.761

0.079

statebrnNorthern Mexico:usdurl

544.221

343.216

1.586

0.114

statebrnPacific Coast:usdurl

-0.227

0.662

-0.343

0.731

statebrnSouth East Mexico:usdurl

-9.147

12.619

-0.725

0.469

statebrnCentral Mexico:occtypeManufacturing

-1578.221

2246.514

-0.703

0.483

statebrnNorthern Mexico:occtypeManufacturing

361183.490

226185.561

1.597

0.111

statebrnPacific Coast:occtypeManufacturing

-311.180

125.454

-2.480

0.013

statebrnSouth East Mexico:occtypeManufacturing

-45.063

360.052

-0.125

0.900

statebrnNorthern Mexico:occtypeProfessional

-777466.540

485988.986

-1.600

0.110

statebrnPacific Coast:occtypeProfessional

-262.200

224.071

-1.170

0.243

statebrnSouth East Mexico:occtypeProfessional

-551.412

514.427

-1.072

0.284

statebrnPacific Coast:occtypeService

-187.867

135.316

-1.388

0.166

statebrnSouth East Mexico:occtypeService

-320.737

420.245

-0.763

0.446

age:usdoc1Legal resident

-11.128

16.157

-0.689

0.491

age:usdoc1Temporary: Tourist/visitor

3.917

17.019

0.230

0.818

age:usdoc1Undocumented

5.985

13.633

0.439

0.661

statebrnPacific Coast:usdoc1Legal resident

-523.494

310.524

-1.686

0.093

statebrnPacific Coast:usdoc1Temporary: Tourist/visitor

-472.147

324.449

-1.455

0.146

statebrnSouth East Mexico:usdoc1Temporary: Tourist/visitor

-181.277

900.820

-0.201

0.841

statebrnPacific Coast:usdoc1Undocumented

-150.866

251.023

-0.601

0.548

statebrnSouth East Mexico:usdoc1Undocumented

295.384

585.080

0.505

0.614

usdurl:usdoc1Legal resident

3.009

1.649

1.825

0.069

usdurl:usdoc1Temporary: Tourist/visitor

2.548

1.646

1.548

0.122

usdurl:usdoc1Undocumented

4.072

1.458

2.794

0.005

```
## Start:  AIC=6198.62
## hhincome ~ sex + age + statebrn + marstat + edyrs + occtype +
##     usdur1 + usdurl + usdoc1 + uscity + sex * usdurl + age *
##     usdurl + age * edyrs + statebrn * edyrs + statebrn * usdurl +
##     occtype * statebrn + usdoc1 * age + usdoc1 * statebrn + usdoc1 *
##     usdurl
##
##                    Df Sum of Sq       RSS    AIC
## - marstat           5    798713 102826911 6192.5
## - uscity            2     14733 102042930 6194.7
## - statebrn:usdoc1   5   1547301 103575499 6196.1
## - statebrn:occtype  7   2437442 104465639 6196.4
## - age:usdoc1        3    892540 102920737 6197.0
## - statebrn:usdurl   4   1445151 103473349 6197.6
## - usdur1            1    210340 102238537 6197.6
## - age:usdurl        1    225226 102253423 6197.7
## - sex:usdurl        1    337346 102365544 6198.3
## <none>                          102028197 6198.6
## - statebrn:edyrs    2   1069840 103098037 6199.8
## - usdurl:usdoc1     3   2402643 104430841 6204.2
## - age:edyrs         1   3051141 105079338 6211.3
##
## Step:  AIC=6192.5
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1 + uscity + sex:usdurl + age:usdurl + age:edyrs +
##     statebrn:edyrs + statebrn:usdurl + statebrn:occtype + age:usdoc1 +
##     statebrn:usdoc1 + usdurl:usdoc1
##
##                    Df Sum of Sq       RSS    AIC
## - uscity            2     10173 102837084 6188.6
## - statebrn:usdoc1   5   1530750 104357660 6189.9
## - statebrn:occtype  7   2443383 105270294 6190.2
## - age:usdoc1        3    944526 103771437 6191.1
## - statebrn:usdurl   4   1422686 104249596 6191.3
## - age:usdurl        1    188407 103015318 6191.4
## - usdur1            1    247729 103074639 6191.7
## - sex:usdurl        1    319842 103146753 6192.0
## <none>                          102826911 6192.5
## - statebrn:edyrs    2   1058066 103884977 6193.6
## - usdurl:usdoc1     3   2484584 105311495 6198.4
## - age:edyrs         1   3373302 106200212 6206.6
##
## Step:  AIC=6188.55
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1 + sex:usdurl + age:usdurl + age:edyrs + statebrn:edyrs +
```

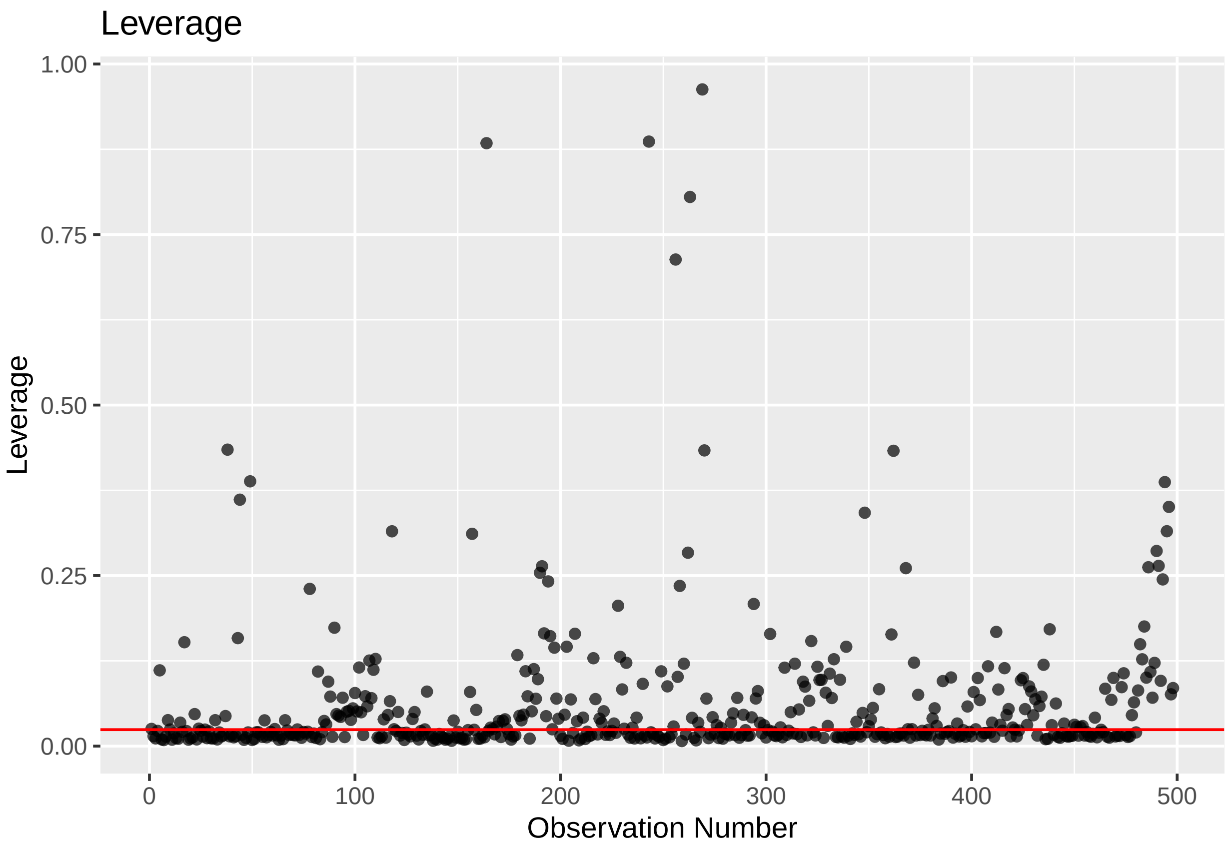
```
##     statebrn:usdurl + statebrn:occtype + age:usdoc1 + statebrn:usdoc1 +
##     usdurl:usdoc1
##
##                    Df Sum of Sq       RSS    AIC
## - statebrn:usdoc1   5   1525065 104362149 6185.9
## - statebrn:occtype  7   2473924 105311008 6186.4
## - age:usdoc1        3    947361 103784445 6187.1
## - statebrn:usdurl   4   1425368 104262451 6187.4
## - age:usdurl        1    193519 103030603 6187.5
## - usdur1            1    244035 103081119 6187.7
## - sex:usdurl        1    317154 103154238 6188.1
## <none>                          102837084 6188.6
## - statebrn:edyrs    2   1068165 103905248 6189.7
## - usdurl:usdoc1     3   2534511 105371595 6194.7
## - age:edyrs         1   3369641 106206725 6202.6
##
## Step:  AIC=6185.88
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1 + sex:usdurl + age:usdurl + age:edyrs + statebrn:edyrs +
##     statebrn:usdurl + statebrn:occtype + age:usdoc1 + usdurl:usdoc1
##
##                    Df Sum of Sq       RSS    AIC
## - statebrn:occtype  9   3009945 107372094 6182.0
## - age:usdoc1        3    906059 105268208 6184.2
## - statebrn:usdurl   4   1428113 105790262 6184.7
## - age:usdurl        1    165149 104527298 6184.7
## - usdur1            1    312173 104674322 6185.4
## - sex:usdurl        1    354542 104716691 6185.6
## <none>                          104362149 6185.9
## - usdurl:usdoc1     3   2292523 106654672 6190.7
## - statebrn:edyrs    4   2751893 107114042 6190.8
## - age:edyrs         1   3217930 107580079 6199.0
##
## Step:  AIC=6182.04
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1 + sex:usdurl + age:usdurl + age:edyrs + statebrn:edyrs +
##     statebrn:usdurl + age:usdoc1 + usdurl:usdoc1
##
##                   Df Sum of Sq       RSS    AIC
## - age:usdurl       1    107689 107479783 6180.5
## - sex:usdurl       1    317883 107689977 6181.5
## - usdur1           1    343670 107715764 6181.6
## <none>                         107372094 6182.0
## - age:usdoc1       3   1557910 108930005 6183.2
## - occtype          3   1575804 108947898 6183.3
## - statebrn:usdurl  4   2191847 109563941 6184.1
## - usdurl:usdoc1    3   2449288 109821382 6187.3
## - statebrn:edyrs   4   3629661 111001755 6190.6
## - age:edyrs        1   3202097 110574192 6194.7
##
## Step:  AIC=6180.54
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdur1 +
##     usdurl + usdoc1 + sex:usdurl + age:edyrs + statebrn:edyrs +
##     statebrn:usdurl + age:usdoc1 + usdurl:usdoc1
```

```
##
##                   Df Sum of Sq       RSS    AIC
## - usdur1           1    400164 107879947 6180.4
## <none>                          107479783 6180.5
## - sex:usdurl       1    629906 108109689 6181.5
## - occtype          3   1555672 109035455 6181.7
## - age:usdoc1       3   1563108 109042891 6181.7
## - statebrn:usdurl  4   2581121 110060904 6184.4
## - usdurl:usdoc1    3   2348044 109827827 6185.3
## - statebrn:edyrs   4   3617967 111097751 6189.0
## - age:edyrs        1   3162532 110642315 6193.0
##
## Step:  AIC=6180.39
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdurl +
##     usdoc1 + sex:usdurl + age:edyrs + statebrn:edyrs + statebrn:usdurl +
##     age:usdoc1 + usdurl:usdoc1
##
##                   Df Sum of Sq       RSS    AIC
## - sex:usdurl       1    416290 108296237 6180.3
## <none>                          107879947 6180.4
## - occtype          3   1478605 109358553 6181.2
## - age:usdoc1       3   1602727 109482674 6181.7
## - usdurl:usdoc1    3   2074169 109954117 6183.9
## - statebrn:usdurl  4   2858610 110738557 6185.4
## - statebrn:edyrs   4   3832434 111712381 6189.8
## - age:edyrs        1   3223397 111103344 6193.1
##
## Step:  AIC=6180.31
## hhincome ~ sex + age + statebrn + edyrs + occtype + usdurl +
##     usdoc1 + age:edyrs + statebrn:edyrs + statebrn:usdurl + age:usdoc1 +
##     usdurl:usdoc1
##
##                   Df Sum of Sq       RSS    AIC
## <none>                          108296237 6180.3
## - occtype          3   1336279 109632517 6180.4
## - age:usdoc1       3   1711825 110008063 6182.1
## - usdurl:usdoc1    3   2120982 110417220 6184.0
## - sex              1   1629464 109925701 6185.7
## - statebrn:usdurl  4   3009678 111305915 6186.0
## - statebrn:edyrs   4   3819971 112116208 6189.6
## - age:edyrs        1   3562596 111858833 6194.4
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	629.277	297.065	2.118	0.035	45.530	1213.024
sexM	327.669	123.480	2.654	0.008	85.025	570.314
age	-22.666	11.074	-2.047	0.041	-44.426	-0.905
statebrnCentral Mexico	2482.855	868.543	2.859	0.004	776.129	4189.581
statebrnNorthern Mexico	-18.793	405.261	-0.046	0.963	-815.149	777.563
statebrnPacific Coast	157.480	95.472	1.649	0.100	-30.127	345.087
statebrnSouth East Mexico	- 185.051	655.663	-0.282	0.778	- 1473.458	1103.356
edyrs	42.483	11.337	3.747	0.000	20.205	64.762
occtypeManufacturing	100.196	62.074	1.614	0.107	-21.783	222.175
occtypeProfessional	208.005	105.018	1.981	0.048	1.641	414.369

term	estimate	std.error	statistic	p.value	conf.low	conf.high
occtypeService	138.882	66.983	2.073	0.039	7.258	270.506
usdurl	-1.914	1.340	-1.429	0.154	-4.548	0.719
usdoc1Legal resident	-244.490	265.390	-0.921	0.357	-765.993	277.013
usdoc1Temporary: Tourist/visitor	-431.169	275.379	-1.566	0.118	-972.302	109.964
usdoc1Undocumented	-406.538	253.226	-1.605	0.109	-904.139	91.064
age:edyrs	2.434	0.620	3.924	0.000	1.215	3.654
statebrnCentral Mexico:edyrs	-304.707	114.163	-2.669	0.008	-529.042	-80.372
statebrnNorthern Mexico:edyrs	14.954	44.830	0.334	0.739	-73.138	103.047
statebrnPacific Coast:edyrs	-38.703	13.223	-2.927	0.004	-64.688	-12.719
statebrnSouth East Mexico:edyrs	10.996	35.425	0.310	0.756	-58.616	80.608
statebrnCentral Mexico:usdurl	10.870	6.326	1.718	0.086	-1.562	23.301
statebrnNorthern Mexico:usdurl	-5.348	1.852	-2.888	0.004	-8.987	-1.709
statebrnPacific Coast:usdurl	-0.856	0.587	-1.460	0.145	-2.009	0.296
statebrnSouth East Mexico:usdurl	-5.475	11.303	-0.484	0.628	-27.686	16.736
age:usdoc1Legal resident	-1.828	14.365	-0.127	0.899	-30.056	26.400
age:usdoc1Temporary: Tourist/visitor	16.945	15.000	1.130	0.259	-12.530	46.419
age:usdoc1Undocumented	17.680	11.604	1.524	0.128	-5.123	40.483
usdurl:usdoc1Legal resident	2.272	1.453	1.564	0.119	-0.583	5.127
usdurl:usdoc1Temporary: Tourist/visitor	1.920	1.498	1.282	0.201	-1.024	4.864
usdurl:usdoc1Undocumented	3.345	1.302	2.570	0.010	0.787	5.902

After backwards selection, including all possible relevant interactions, our model contains the following variables: sex, age, edyrs, usdurl, usdoc1, occtype, statebrn. It also includes these interactions: age & edyrs, edyrs & statebrn, usdurl & statebrn, age & usdoc1, and usdurl & usdoc1.



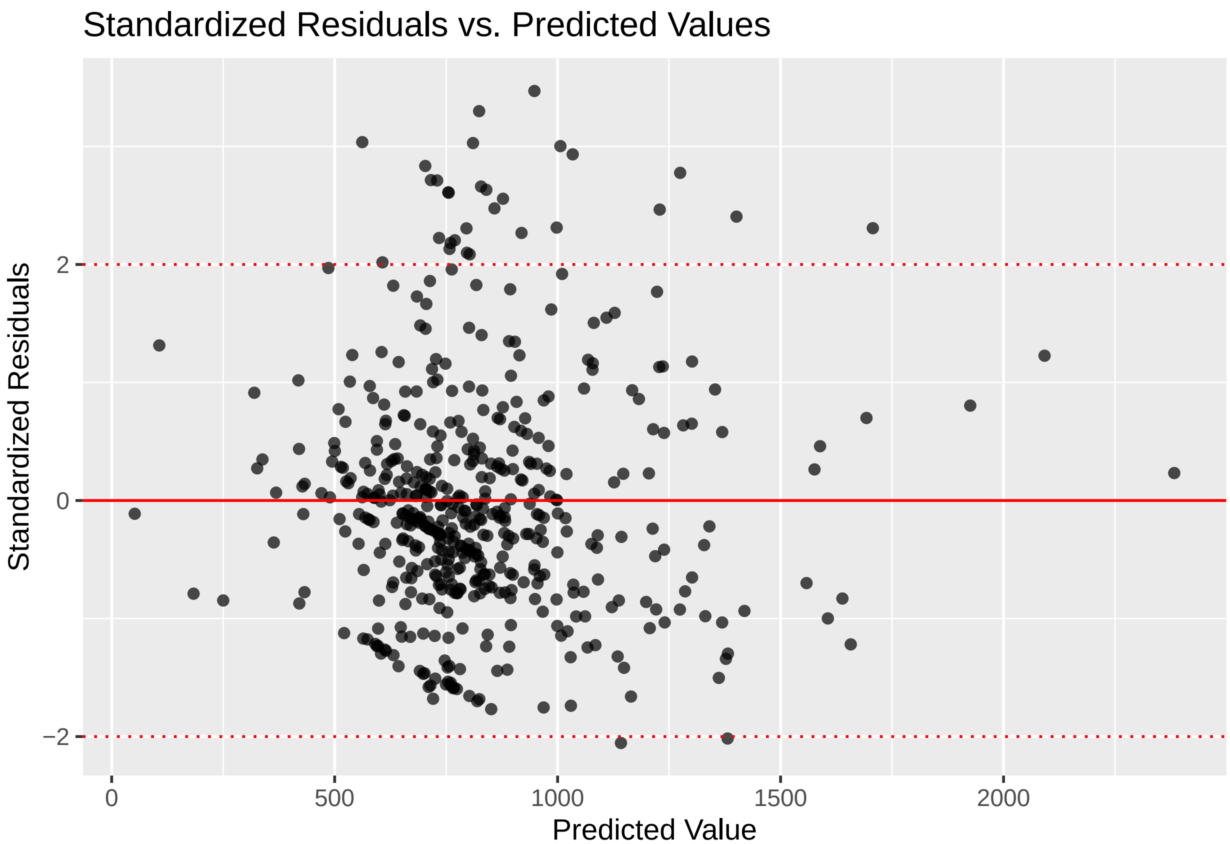

```
## [1] 0.4678715
```

Just under half of our observations are high leverage points, meaning that their combinations of values for the predictor variables are very far from the typical combinations in the data. Because human circumstances and economic conditions are often so extremely variable, we would not expect most migrants to share common values for the predictor variables.

We can look at the four observations with the highest leverage:

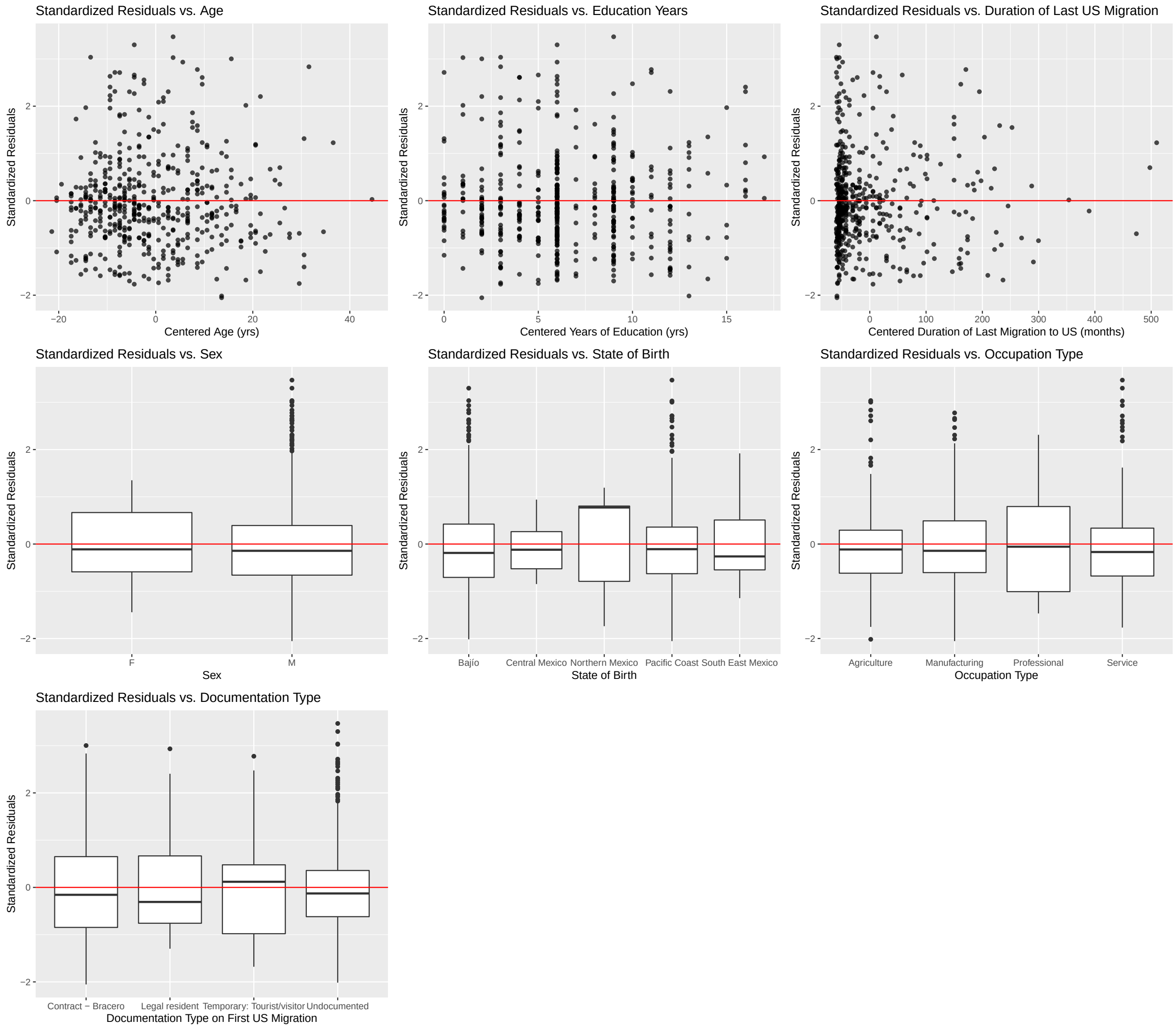
```
## # A tibble: 5 x 16
##   hhincome sex      age statebrn edyrs occtype usdurl usdoc1 .fitted
##      <dbl> <chr>  <dbl> <chr>    <dbl> <chr>    <dbl> <chr>    <dbl>
## 1     2421 M       6.58 Central~     5 Manufa~   41.7 Undoc~   2383.
## 2     1000 M      -2.42 Central~     5 Manufa~  -54.3 Undoc~   1137.
## 3       32 M      14.6  Pacific~     5 Manufa~  300.  Contr~    250.
## 4       16 M     -10.4  Norther~    14 Profes~  270.  Undoc~    184.
## 5     2000 M      -9.42 Norther~    16 Profes~  -48.3 Legal~   1925.
## # ... with 7 more variables: .se.fit <dbl>, .resid <dbl>, .hat <dbl>,
## #   .sigma <dbl>, .cooksd <dbl>, .std.resid <dbl>, obs_num <int>
```

Within the individuals in the data with high leverage, two are highly educated professionals, and three have 5 years of education and work in manufacturing jobs. All are male. Age, documentation, and duration of migration vary. These points are potentially, but not certainly, influential points, so we use other methods to sort out influential points.




```
## [1] 0.062249
```

The 6% of our observations with standardized residuals of magnitude greater than 2 should be examined more closely- these are outliers, but they may not have an impact on the regression line. We can look plots of the standardized residuals versus all of our predictors.

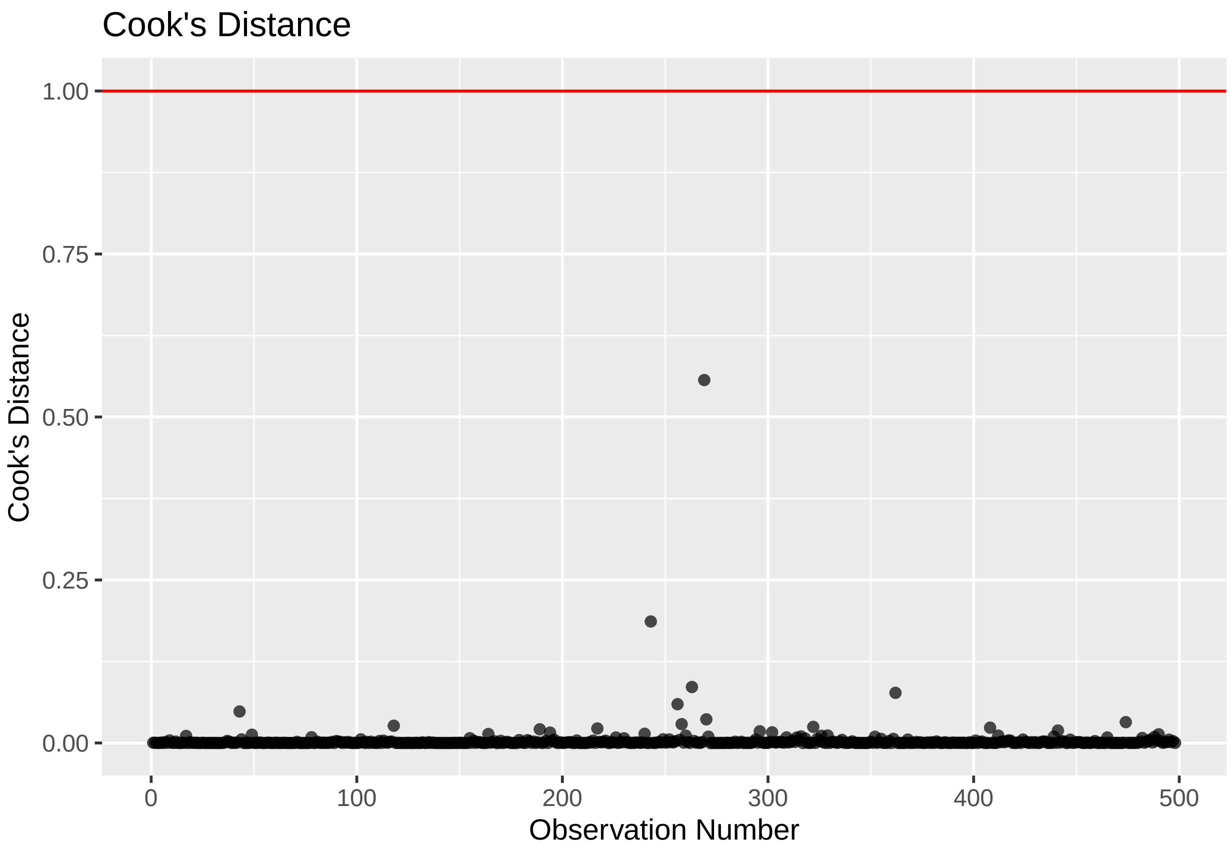


Plots of the standardized residuals for each predictor variable reveal that, for the most part, our data satisfies the constant variance assumption.

```
## [1] 481.0428
```

```
## # A tibble: 1 x 1
##   sigma_est
##       <dbl>
## 1      371.
```

The estimate of our regression standard deviation using all observations is 481.0428, whereas the standard deviation estimate without points with large magnitude standardized residuals is 370.9477. Removing points with large magnitude standardized residuals would affect our conclusions by decreasing the standard error associated with our model coefficients, however, we do not want to damage our model's integrity and explanatory power by removing too much human variability from the observations we base it on. We will examine Cook's Distance to see if any observations have excessive overall impact or significantly affect the estimated coefficients when removed.



No observations have a Cook's Distance greater than 1, thus none of the high leverage points exert significantly greater influence on the final coefficients of our model than the other points and could distort our explanations.

```
## # A tibble: 29 x 2
##    names                        x
##    <chr>                    <dbl>
##  1 sexM                      1.33
##  2 age                      34.4
##  3 statebrnCentral Mexico   19.3
##  4 statebrnNorthern Mexico   3.51
##  5 statebrnPacific Coast     4.89
##  6 statebrnSouth East Mexico 34.0
##  7 edyrs                     3.85
##  8 occtypeManufacturing      2.00
##  9 occtypeProfessional       1.59
## 10 occtypeService            1.98
## # ... with 19 more rows
```

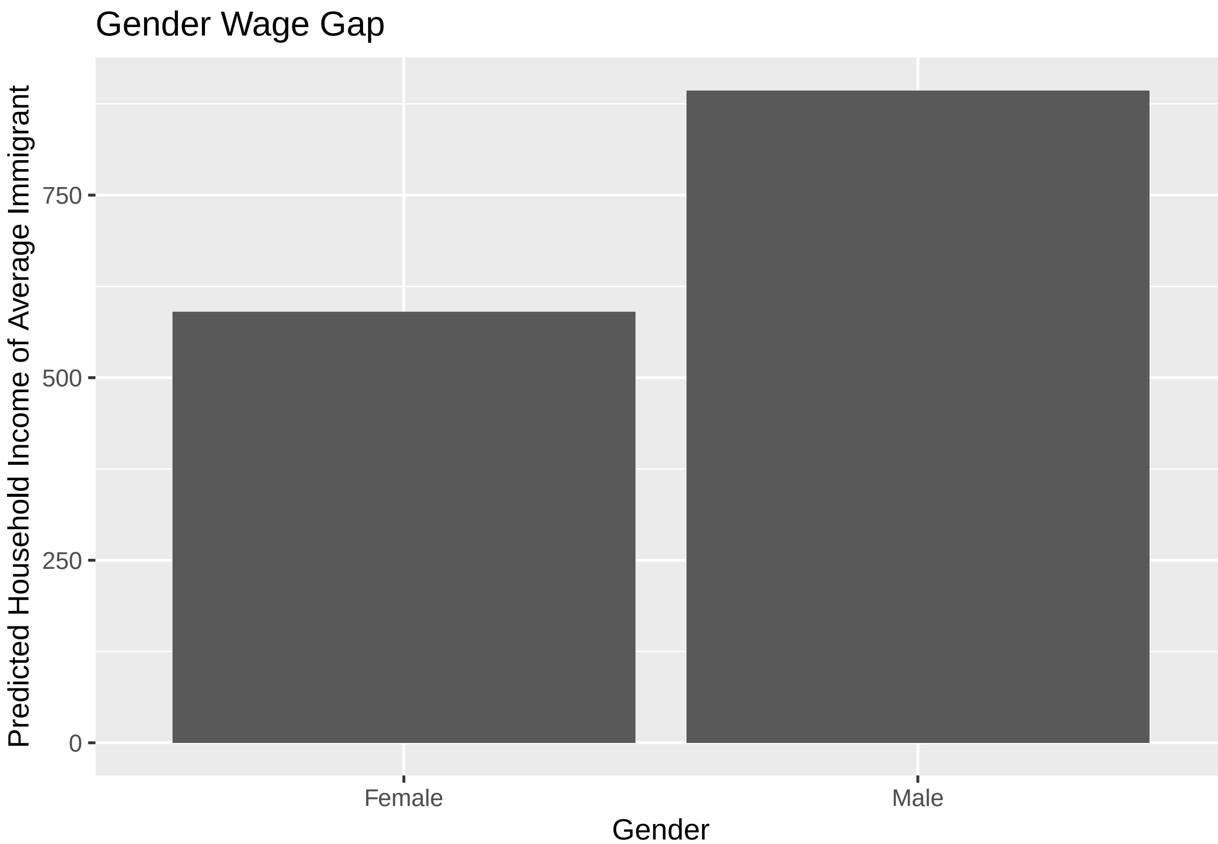
There appear to be several coefficients which exhibit dangerously high multicollinearity. This is discussed in Section 2.

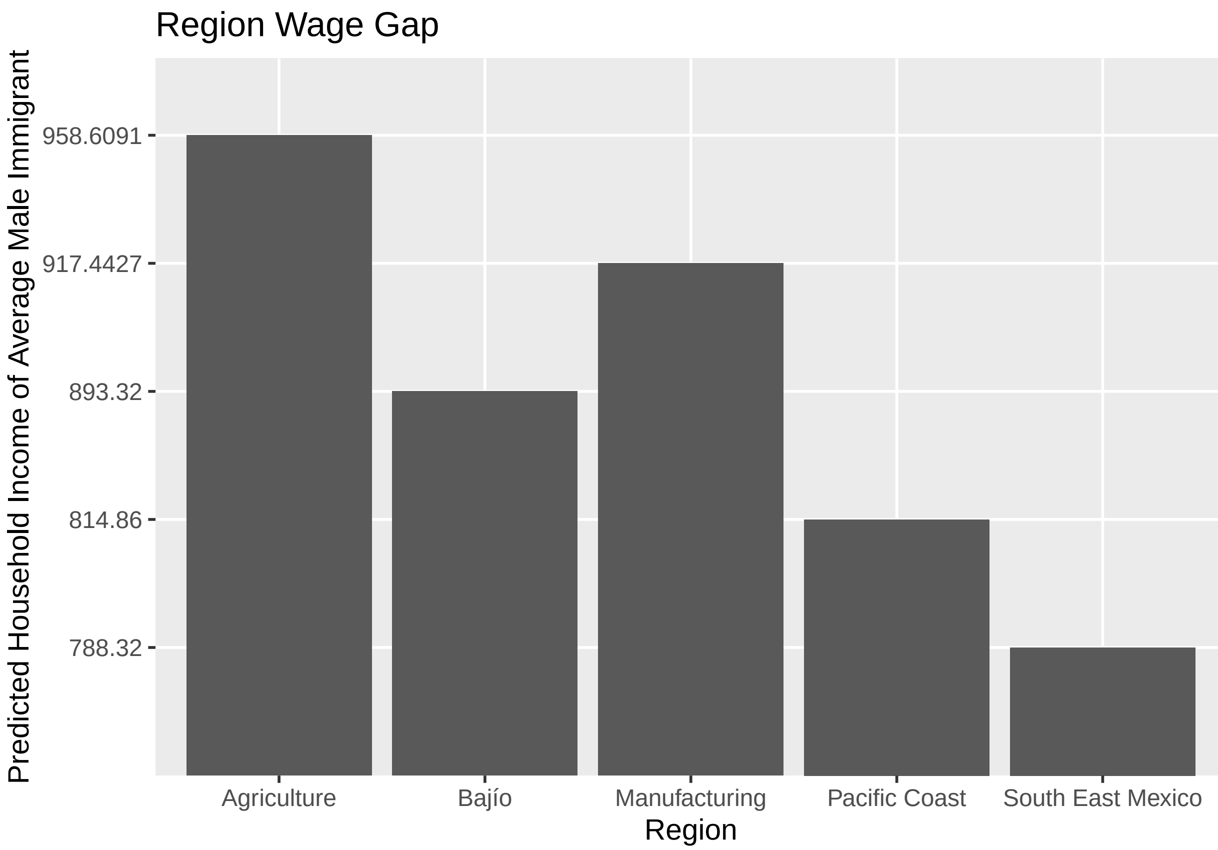
```
## [1] 0.1810094
```

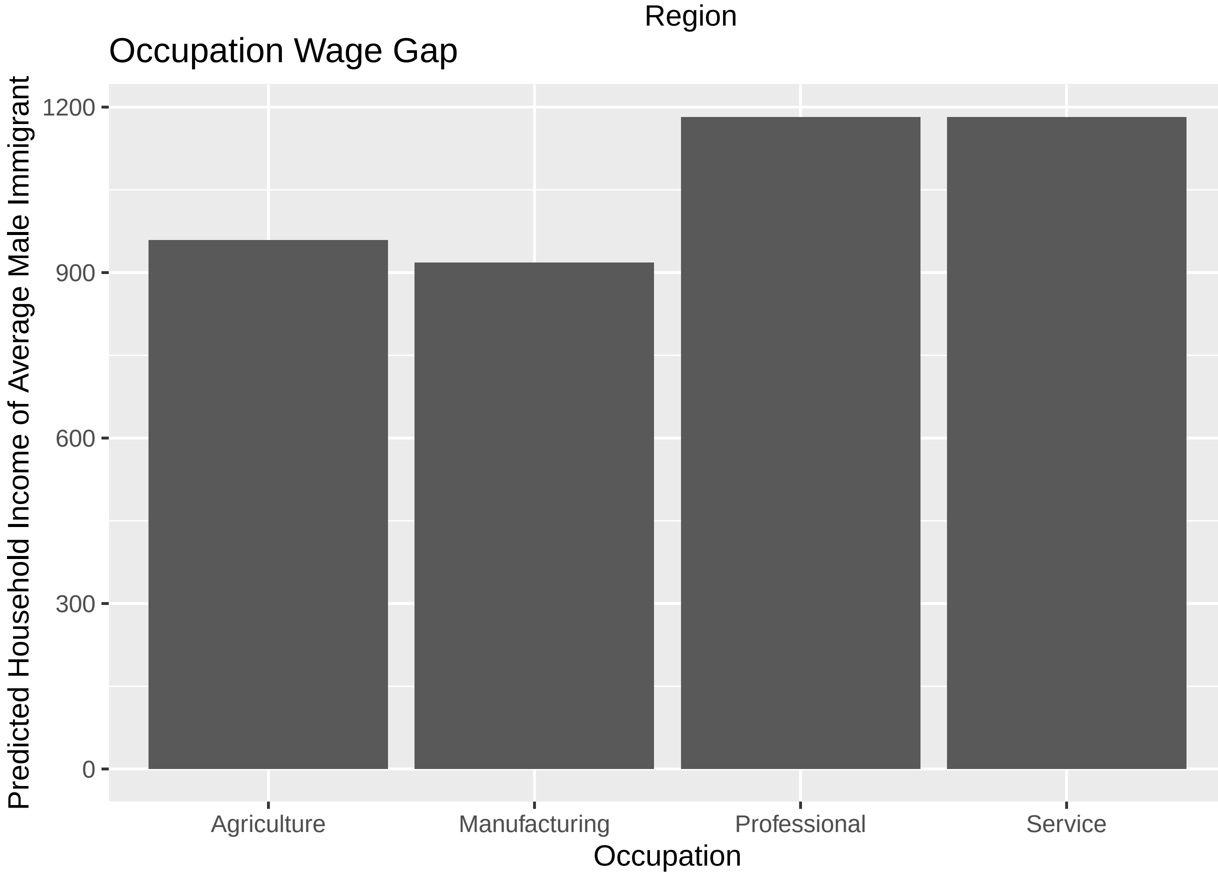
The adjusted R-squared for our final model is 0.181. This means the approximately 18% of the variation in household income is well-accounted for by our model.

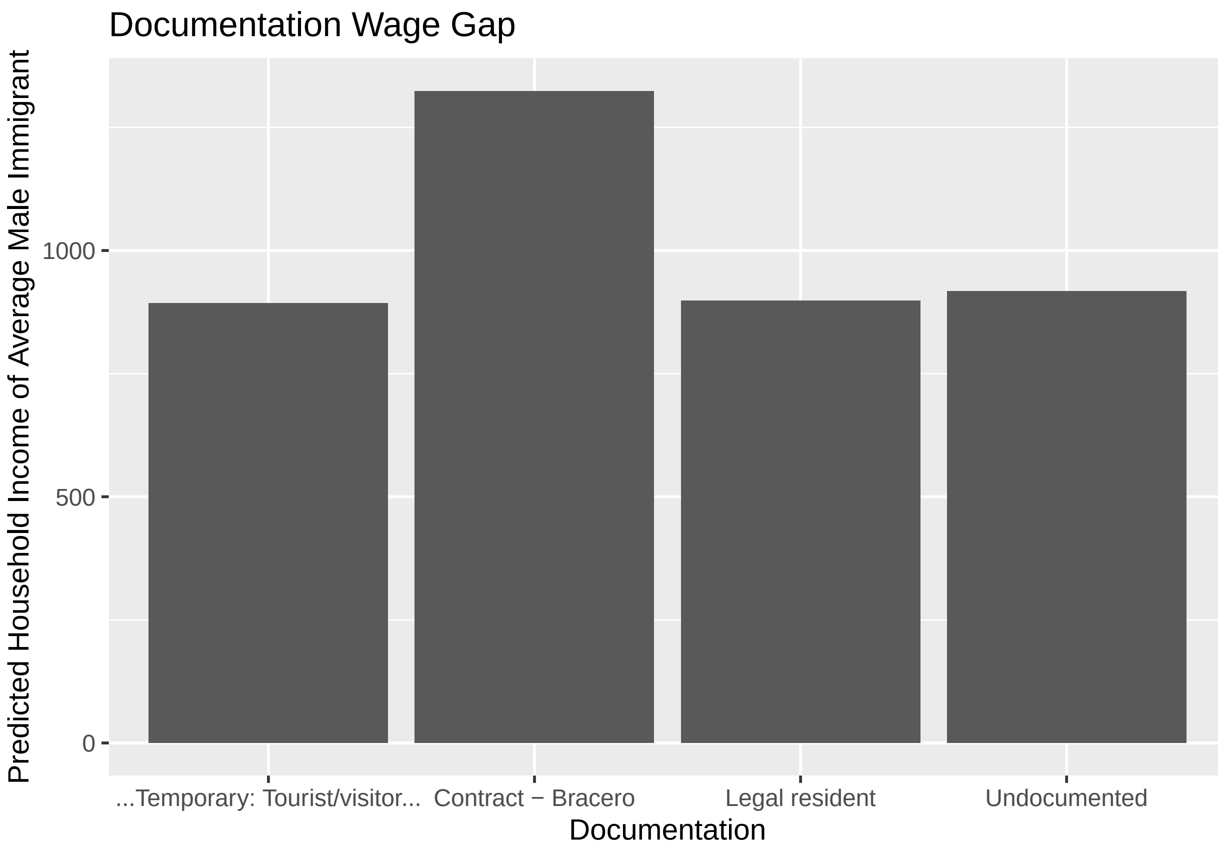
5.7 Gender Wage Gaps

```
##   Gender pred_hhincome
## 1   Male        893.32
## 2 Female        590.11
```




Region Wage Gap
Predicted Household Income of Average Male Immigrant
958.6091
917.4427
893.32
814.86
788.32
Agriculture
Bajío
Manufacturing
Pacific Coast
South East Mexico
Region


Occupation Wage Gap
Predicted Household Income of Average Male Immigrant
1200
900
600
300
0
Agriculture
Manufacturing
Professional
Service
Occupation


Documentation Wage Gap
Predicted Household Income of Average Male Immigrant
0
500
1000
...Temporary: Tourist/visitor...
Contract − Bracero
Legal resident
Undocumented
Documentation