Financial Independence Survey - Logistic Regression Model

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1 Overview

The objective of this project is to address the research question:
What factors contribute to an individual's perception of financial independence?
To accomplish this objective, we will perform logistic regression analysis using a dataset that is a subset of the official results from the 2020 Financial Independence Survey on Reddit. This subset includes responses from individuals who represent themselves (excluding contributions from other household members) and excludes responses from retired individuals. The dataset encompasses **1,998 rows** and **65 variables**, covering information such as income contributors, the financial impact of the pandemic, political affiliation, demographics, details about financial independence, employment status, and various financial aspects. The data has been sourced from Reddit. For additional details regarding the data dictionary and source information, please refer to the www.openintro.org website.
In our original dataset, 147 individuals, which accounts for 8% of our sample, reported considering themselves financially independent. Therefore, we have unbalanced data, which we should take into consideration in our future analyses.

2 Data cleaning

In the data cleaning process, the following transformations were implemented. For more details on the specific variables that experienced these transformations, please refer to the appendix page.

- The dependent variable **fin_indy** (Are you financially independent?) was transformed from a string variable to a binary numeric variable (0 and 1).
- The variable **political** had 24 categories, which were reduced to 4: 'Democrat,' 'Libertarian Party,' 'Republican,' and 'Other,' because the data had many categories with very few observations. Finally, it was transformed from string to factor.
- The variable **age** was transformed from a string variable to a numeric variable to simplify analysis, with each category assigned a corresponding numeric value (1-8) to represent age brackets.
- The variable **edu** had 11 categories, which were reduced to 4: "High School or Less", "Some College or Trade School", "Bachelor's or Associate's Degree", "Doctorate or Master's Degree", because the data had many categories with very few observations. Then, it was transformed from string to factor.
- The variable **housing** (What is your current housing situation?) had 19 categories, which were reduced to 2: "Own", "Not Own", because the data had many categories with very few observations. Finally, it was transformed from string to factor.
- Out of a total of 29 variables, which constituted numeric-type variables such as Children Expenses, Luxury Expenses, Transportation Expenses, Taxes, Medical Debt, etc., it was observed that they did not contain the number 0 but did have many NA values. The assumption was made that individuals who responded with NA in fields such as Children Expenses did so because they had no associated expenses in that category. For this reason, in these 29 variables, NA values were replaced with 0. The complete detail of the variables can be reviewed on the appendix page.
- The variable **total_assets** was created, which is formed by the sum of 8 variables such as cash, investment accounts, crypto, etc. For more details, refer to the appendix.
- The variable **total_debts** was created, which is formed by the sum of 7 variables such as student loans, mortgage, medical debt, etc. For more details, refer to the appendix.
- The variable **total_expenses** was created, which is formed by the sum of 12 variables such as necessities expenses, children expenses, transportation expenses, etc.
- Finally, observations with NA values for any of the above variables were removed, resulting in 11 observations out of the original total of 1,998, leaving us with 1,987 final observations.

3 Modeling

3.1 Logistic Regression Model

To address our research question, we will employ a Logistic Regression Model. This model is suitable for this situation as it allows us to examine how various predictor variables influence the probability of an individual perceiving financial independence. Given that the variable of interest is binary (yes/no), logistic regression will provide us with estimations of log probabilities and coefficients that will aid in understanding the direction and strength of the relationship between the considered factors and the perception of financial independence.

3.2 Variable Selection

After analyzing the variables provided in the dataset, those that could be considered to influence the financial independence variable were identified. The following variables were selected a priori as predictors: **Age**, **Political** (With which political party do you most closely identify?), **Education** (What is the highest level of education you have completed?), **Housing** (What is your current housing situation? **Rent**, Own…) , **Total Debts**, **Total Assets**, **Total Expenses**, **2020 Gross Income**, **2020 Investments, 2020 savings**.

For the variable age, it is expected that as a person gets older, they are more likely to have achieved greater economic stability and, therefore, are more prone to being financially independent. Regarding the political variable, it is anticipated that individuals belonging to parties that oppose, for example, tax increases, see economic independence as feasible through their own assets. It is expected that with higher education, there is a greater likelihood of being financially independent. Concerning the housing variable, it is expected that owning a home will significantly impact the dependent variable. In the case of the variables debt, assets, expenses, 2020 income, and 2020 investments, they are considered closely related to the dependent variable, as the available wealth of an individual, i.e., income minus expenses, assets minus liabilities, will determine whether they can achieve economic independence or not.

4 Results

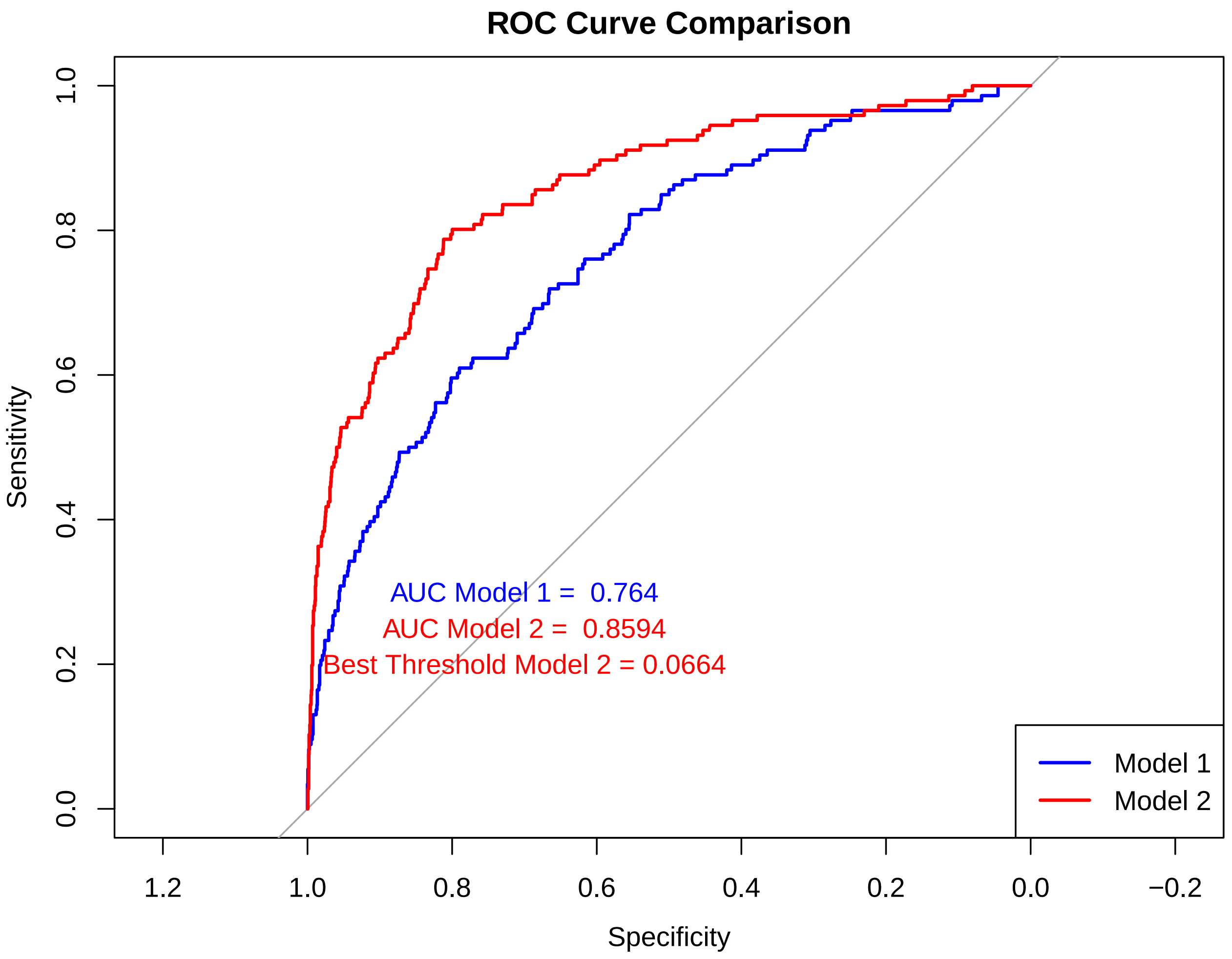
4.1 Model results

```
Call:
glm(formula = factor(fin_indy) ~ age + political_grouped + edu_grouped +
    housing_grouped + total_debts + total_assets + total_expenses +
    `2020_gross_inc` + `2020_invst_save`, family = "binomial",
    data = reddit_finance_sub2)

Coefficients:
                                            Estimate Std. Error z value
(Intercept)                               -4.585e+00  7.490e-01  -6.121
age                                        4.441e-01  7.067e-02   6.284
political_groupedLibertarian Party         2.788e-01  4.194e-01   0.665
political_groupedOther                     4.535e-01  2.212e-01   2.051
political_groupedRepublican                7.911e-01  3.065e-01   2.581
edu_groupedSome College or Trade School   -1.292e+00  8.583e-01  -1.506
edu_groupedBachelor's or Associate's Degree -6.132e-01  6.904e-01  -0.888
edu_groupedDoctorate or Master's Degree   -5.694e-01  6.968e-01  -0.817
```

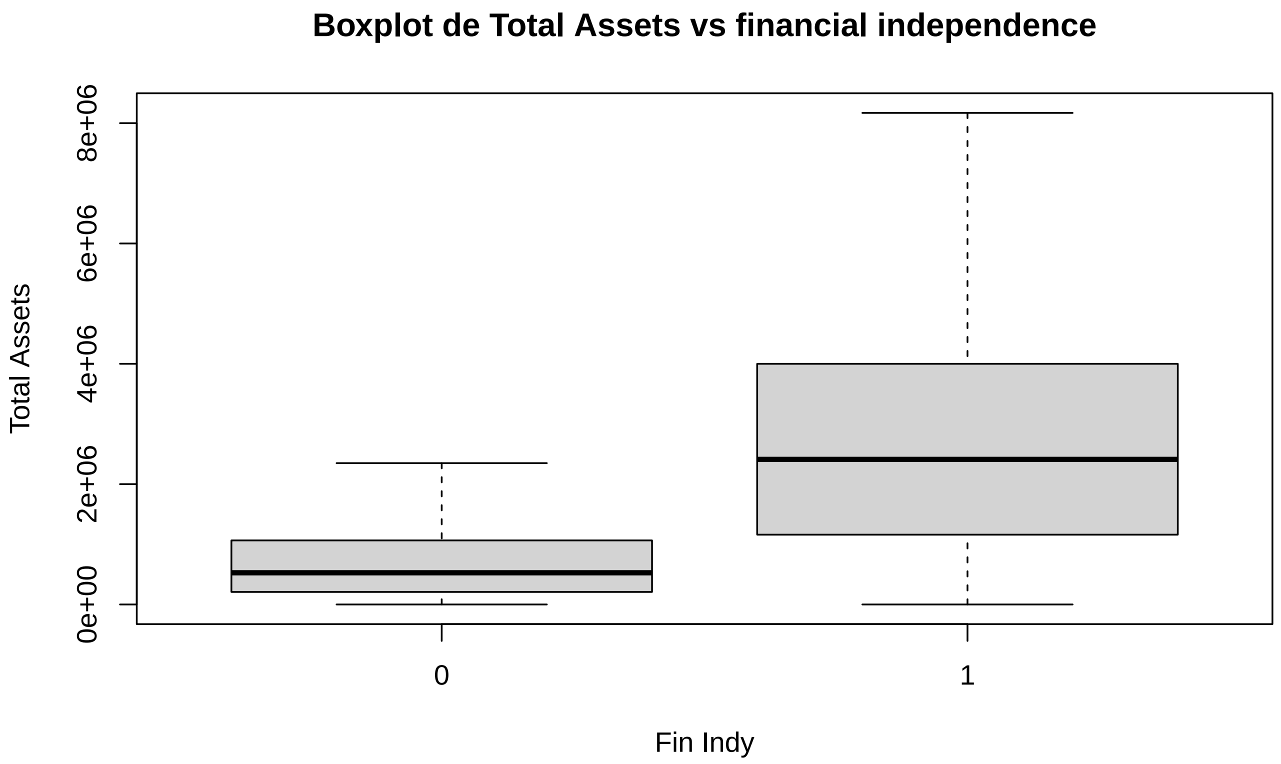
```
housing_groupedOther                        -1.164e+01  4.252e+02  -0.027
housing_groupedOwn                          -7.762e-02  2.431e-01  -0.319
total_debts                                 -1.551e-06  4.303e-07  -3.604
total_assets                                 5.117e-07  7.025e-08   7.284
total_expenses                              -2.515e-06  9.701e-07  -2.592
`2020_gross_inc`                             1.034e-06  5.952e-07   1.737
`2020_invst_save`                           -2.230e-06  1.266e-06  -1.762
                                            Pr(>|z|)    
(Intercept)                                 9.29e-10 ***
age                                         3.29e-10 ***
political_groupedLibertarian Party          0.506296    
political_groupedOther                      0.040301 *  
political_groupedRepublican                 0.009852 ** 
edu_groupedSome College or Trade School     0.132158    
edu_groupedBachelor's or Associate's Degree 0.374383    
edu_groupedDoctorate or Master's Degree     0.413827    
housing_groupedOther                        0.978169    
housing_groupedOwn                          0.749489    
total_debts                                 0.000314 ***
total_assets                                3.25e-13 ***
total_expenses                              0.009533 ** 
`2020_gross_inc`                            0.082349 .  
`2020_invst_save`                           0.078138 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1042.89  on 1983  degrees of freedom
Residual deviance:  794.55  on 1969  degrees of freedom
AIC: 824.55

Number of Fisher Scoring iterations: 13
```

Age exhibits a positive association, indicating that as individuals age, the likelihood of financial independence increases. Affiliation with the Republican Party is associated with higher odds of financial independence compared to the reference category. Education categories show no statistically significant effects. Regarding housing, individuals with "Other" housing arrangements are more likely to be financially independent, while owning or renting does not show significant effects. Notably, variables related to financial status, such as total assets and total debts, demonstrate significant impacts, with higher assets and lower debts associated with increased odds of financial independence. The model's goodness of fit is evident from the lower residual deviance compared to the null deviance. Overall, the findings highlight the multifaceted nature of factors contributing to financial independence.
A lower AIC value, specifically 820.88, implies a favorable balance between the model's capacity to fit the data and its simplicity. This suggests that the logistic regression model effectively captures the data patterns considering its complexity.

4.2 ROC Curve



Upon observing the ROC curve, it becomes evident that the model's discriminative performance is robust, as indicated by the AUC value of 0.861. Notably, at the specific threshold of 0.067, a distinct point on the curve is identified, emphasizing the tailored balance achieved between the true positive and false positive rates. This nuanced insight from the ROC analysis underscores the model's ability to effectively classify instances with a refined understanding of the trade-off between positive predictions and potential errors Additionally, the confusion matrix was computed (see in the appendix). The confusion matrix results reveal that, despite the low prevalence of positive responses, the model achieves an accuracy of 79.82%. Sensitivity and specificity metrics are crucial in this imbalanced context, showcasing the model's ability to detect positive and negative instances, respectively. The low precision (23.93%) suggests that positive predictions should be approached with caution. Although the Kappa coefficient implies some agreement beyond chance (0.2888), it is vital to consider metrics adjusted for imbalance, such as sensitivity and specificity, for a more comprehensive assessment of the model's performance.
After generating our model, we can, for example, observe the behavior of one of the variables that turned out to be most influential in predicting our dependent variable, Total Assets. We can see how the group of individuals who are financially independent indeed has significantly higher assets.



5 Conclusion and Future work

Given the previously results, the logistic regression model indicates a positive association between age and financial independence, while Republican Party affiliation, “Other” housing arrangements, and favorable financial statuses significantly contribute. The model’s performance, reflected in the AUC of 0.861 and nuanced insights from the ROC analysis, underscores its ability to discern positive instances. However, the confusion matrix highlights the challenge of imbalanced classes, urging caution regarding positive predictions. Despite an accuracy of 79.82%, the evaluation of the model’s practical utility should prioritize precision and sensitivity.

The conducted analysis provides us with a model to identify factors influencing people’s perception of financial independence. While the results make sense, it’s crucial to consider study limitations. One important aspect is the potential presence of confounding variables, such as age, which could impact an individual’s levels of assets, liabilities, and income, factors theoretically influencing financial independence. A future analysis could explore the results by removing the confounding variable of age to more precisely assess the impact of the specific factors considered in our model.

Furthermore, it would be relevant to conduct cross-validation analyses to evaluate the model’s generalization capacity to unseen data. This helps verify if the model is robust and can be applied to new samples, crucial for ensuring the reliability of conclusions and the practical utility of the model in different contexts.

In conclusion, by addressing these considerations, we can enhance the robustness and applicability of our model to understand the perception of financial independence.

6 Appendix

6.1 Variable Transformation

Variable	**Transformation**
political	• From 24 original categories, it was grouped into 4: “Democrat” “Libertarian Party” “Republican” “Other” –> (“American Solidarity Party”,“Citizens Party of the United States”,“Communist Party USA”,“Constitution Party”,“Freedom Socialist Party”,“Green Party”,“Humane Party”,“Independent American Party”,“Legal Marijuana Now Party”,“N/A”,“NA”,“National Socialist Movement”,“None”,“Objectivist Party”,“Peace and Freedom Party”,“Socialist Action”,“Socialist Alternative”,“Socialist Equality Party”,“Socialist Party USA”,“United States Marijuana Party”,“United States Pirate Party”,“Workers World Party”) • Transformed into a factor.
age	• It was transformed from string to numeric (1-10)
edu	• From 11 original categories, it was grouped into 4: “High School or Less” –> (“High School diploma / GED”, “Less than high school”, “Some high school”) “Some College or Trade School” –> (“Some college, no degree”, “Trade School Degree”) “Bachelor’s or Associate’s Degree” –> (“Associate’s Degree”, “Bachelor’s Degree”) “Doctorate or Master’s Degree” –> (“Doctorate / Post Graduate”, “Doctorate / Post-Graduate”, “Graduate degree”) • Transformed into a factor.
fin_indy	• It was transformed from string to binary

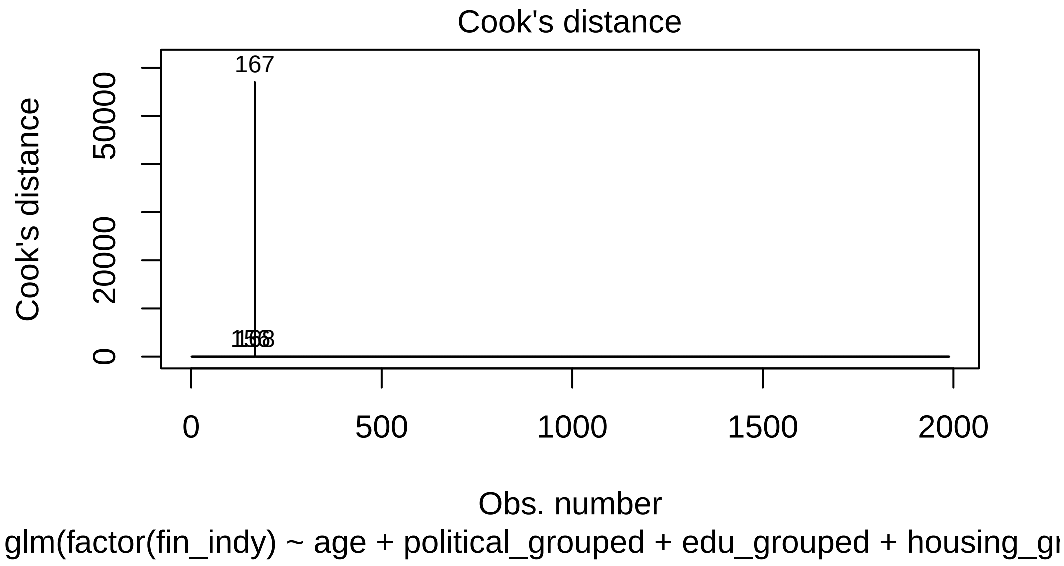
housing	• From the original 19 categories, it was grouped into 2: “Own” –> (Own”, “Own a house but currently living in a RV”, “Own a house that I rent out but I rent an apartment in another state”, “Rent and own”, “Rent my apartment, but own a home I rent out”, “Rent temporarily while building new home”) “Not Own” –> (“Government housing”, “Homeless”, “House owned by parents”, “Houseless/nomadic - living in a car voluntarily”, “Live with family or friends”, “Live with family while building a house”, “Live with partner and split costs of owning”, “Live with partner in their house”, “Liveaboard boat”, “Living with parents”, “NA”, “Own and live in a van”, “Provided by employer or school”, “Rent”) • Transformed into a factor.
home_value	• NA replaced with 0 • sum in total_assets variable
broke rage_accts_tax	• NA replaced with 0 • sum in total_assets variable
retire ment_accts_tax	• NA replaced with 0 • sum in total_assets variable
cash	• NA replaced with 0 • sum in total_assets variable
invst_accts	• NA replaced with 0 • sum in total_assets variable
spec_crypto	• NA replaced with 0 • sum in total_assets variable
invs t_prop_bus_own	• NA replaced with 0 • sum in total_assets variable
other_val	• NA replaced with 0 • sum in total_assets variable
student_loans	• NA replaced with 0 • sum in total_debts variable

mortgage	• NA replaced with 0 • sum in total_debts variable
auto_loan	• NA replaced with 0 • sum in total_debts variable
credi t_personal_loan	• NA replaced with 0 • sum in total_debts variable
medical_debt	• NA replaced with 0 • sum in total_debts variable
invst_pr o p_bus_own_debt	• NA replaced with 0 • sum in total_debts variable
other_debt	• NA replaced with 0 • sum in total_debts variable
2020_gross_inc	• NA replaced with 0
2 0 20_housing_exp	• NA replaced with 0 • sum in total_expenses variable
202 0_utilities_exp	• NA replaced with 0 • sum in total_expenses variable
2 020_transp_exp	• NA replaced with 0 • sum in total_expenses variable
2020_n ecessities_exp	• NA replaced with 0 • sum in total_expenses variable
2020_lux_exp	• NA replaced with 0 • sum in total_expenses variable
2020_child_exp	• NA replaced with 0 • sum in total_expenses variable

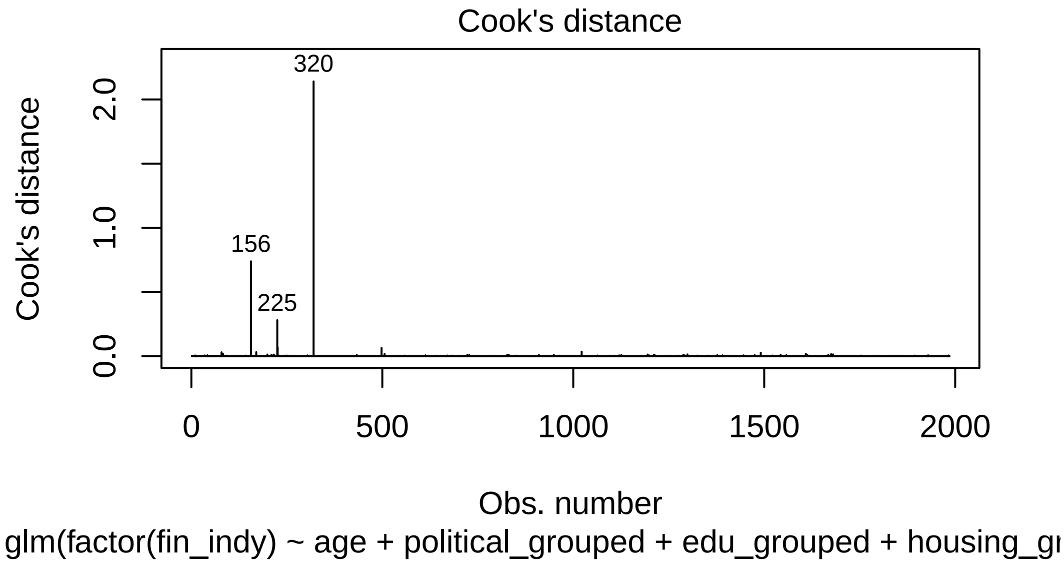
2 020_debt_repay	• NA replaced with 0 • sum in total_expenses variable
2 020_invst_save	• NA replaced with 0
2020_charity	• NA replaced with 0 • sum in total_expenses variable
2020_ healthcare_exp	• NA replaced with 0 • sum in total_expenses variable
2020_taxes	• NA replaced with 0 • sum in total_expenses variable
2020_edu_exp	• NA replaced with 0 • sum in total_expenses variable
2020_other_exp	• NA replaced with 0 • sum in total_expenses variable

6.2 Cook's distance

6.2.1 Model 1



6.2.2 Model 2



6.3 Confusion Matrix

6.3.1 Model 2

```
Confusion Matrix and Statistics

          Reference
Prediction   No  Yes
       No  1474   31
       Yes  364  115
                                          
               Accuracy : 0.8009          
                 95% CI : (0.7826, 0.8183)
    No Information Rate : 0.9264          
    P-Value [Acc > NIR] : 1               
                                          
                  Kappa : 0.2876          
                                          
 Mcnemar's Test P-Value : <2e-16          
                                          
            Sensitivity : 0.78767         
            Specificity : 0.80196         
         Pos Pred Value : 0.24008         
         Neg Pred Value : 0.97940         
              Precision : 0.24008         
                 Recall : 0.78767         
                     F1 : 0.36800         
             Prevalence : 0.07359         
         Detection Rate : 0.05796         
   Detection Prevalence : 0.24143         
      Balanced Accuracy : 0.79481         
                                          
       'Positive' Class : Yes             
```