Chicago Housing

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```
rm(list = ls())
library(tidyverse)
library(stargazer)
library(readxl)
library(knitr)
library(lubridate)
library(dplyr)
library(devtools)
library(sf)
library(janitor)
library(MASS)
knitr::opts_chunk$set(echo = FALSE)
```

Reading in, cleaning, and combining data

Reading in data

Cleaning main datasets

Adding redlining data and zipcodes

Data visualizations

Creating dataframe for visualization by zip code

```
## # A tibble: 3 x 7
           loan_total white_percent_avg black_percent_avg latino_percent_avg
     <chr>
               <dbl>
                                  <dbl>
                                                    <dbl>
                                                                        <dbl>
## 1 60614 7683047000
                                  0.791
                                                    0.0368
                                                                       0.0796
## 2 60647 5446853000
                                  0.530
                                                   0.0504
                                                                       0.346
## 3 60657 5118651000
                                  0.812
                                                    0.0279
                                                                       0.0723
## # ... with 2 more variables: asian_percent_avg <dbl>, majority_race <chr>
```

Recreating WBEZ figure. Map of Chicago zip codes color coded by the dollar amount of mortgage loans made to that area from 2012-2018.

```
## pdf
## 2
## pdf
## 2
```

```
## # A tibble: 3 x 11
##
     census_tract loan_total white_percent_avg black_percent_avg latino_percent_avg
                                         <dbl>
                                                           <dbl>
## 1 17031330100 1747818000
                                         0.482
                                                          0.215
                                                                              0.0611
## 2 17031081800 1010495000
                                         0.826
                                                          0.0114
                                                                              0.0549
## 3 17031833100
                  835049000
                                         0.606
                                                          0.115
                                                                              0.0892
## # ... with 6 more variables: asian_percent_avg <dbl>, tract_pop <dbl>,
      med_family_income <dbl>, avg_loan_amount <dbl>, majority_race <chr>,
## #
      id <int>
```

Creating redlining ranking for 2012-2018 census tracts

```
## [1] 795

## [1] 742

##

## 1 2 3 4

## 4 66 382 290

##

## 1 2 3 4

## 0.005390836 0.088948787 0.514824798 0.390835580
```

Table comparing number of census tracts in each of the four HOLD grades.

```
##
       2
            3 4
    1
    3 61 387 291
##
                     ranking_2010
                                    1
## redline_1930_value
## 1
                                           3
                                    0
                                       1
## 2
                                       6 46 14
## 3
                                    0 20 222 140
                                      34 116 137
## 4
```

Regression 1:

##

```
## Call:
## polr(formula = as.factor(ranking_2010) ~ redline_1930_value,
##
      data = for_regression, Hess = TRUE)
##
## Coefficients:
                       Value Std. Error t value
##
## redline_1930_value 0.3744
                                 0.1122
                                          3.336
##
## Intercepts:
      Value
##
              Std. Error t value
## 1|2 -5.3991 1.0540
                          -5.1223
## 2|3 -1.1960 0.3782
                          -3.1624
```

3|4 1.6617 0.3768 4.4103

##

Residual Deviance: 1351.42

AIC: 1359.42

Table 1:

	Dependent variable:	
	loans_millions Total home loan amount by Census Tract	
	(1)	(2)
Continous Redline Grade	19.532*** (3.124)	
Redline Categories	, ,	16.785*** (2.920)
Tract Population	$0.014^{***} (0.001)$	0.014*** (0.001)
Average Family Income	-0.012***(0.004)	$-0.012^{***}(0.004)$
Average Loan Amount	$0.0002^{***} (0.00001)$	0.0002*** (0.00001)
Majority Black	-14.920^{**} (6.126)	-15.488** (6.157)
Majority Latino	-24.126^{***} (6.185)	-24.174^{***} (6.211)
Majority White	74.224*** (5.954)	73.269*** (5.967)
Observations	740	740
\mathbb{R}^2	0.666	0.663
Adjusted R ²	0.663	0.660
Residual Std. Error ($df = 732$)	47.880	48.069
F Statistic (df = 7 ; 732)	208.449***	205.997***

Note:

*p<0.1; **p<0.05; ***p<0.01

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Sat, May 28, 2022 - 22:41:53

Table 2:

	Dependent variable:	
	ranking_2010	
redline_1930_value	0.374*** (0.112)	
Observations	740	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Regression 2: Past category of HOLC grade as predictor for modern recreated distribution

```
##
## Call:
## lm(formula = ranking_2010 ~ value_2 + value_3 + value_4, data = for_regression)
##
## Residuals:
## Min   1Q Median   3Q Max
## -2.3507 -0.3141 -0.3141   0.6493   0.9000
```

```
##
## Coefficients: (1 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.35069
                          0.03646 91.897 < 2e-16 ***
## value 2
              -0.25069
                          0.08246
                                  -3.040 0.00245 **
## value 3
              -0.03656
                          0.04829
                                   -0.757 0.44924
## value_4
                                       NA
                    NA
                               NA
                                                NA
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.6188 on 737 degrees of freedom
## Multiple R-squared: 0.01249,
                                   Adjusted R-squared: 0.009806
## F-statistic: 4.659 on 2 and 737 DF, p-value: 0.009755
##
## Call:
## lm(formula = loan_total ~ HRS2010 + majority_race, data = for_regression)
## Residuals:
##
         Min
                     1Q
                            Median
                                           30
                                                     Max
## -153187631 -22815369
                          -6976629
                                     17077087
                                              366055369
##
## Coefficients:
##
                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                       19164792 12713592
                                            1.507 0.132
                                            4.047 5.73e-05 ***
## HRS2010
                       14233205
                                   3516583
## majority_raceblack -50092493
                                   6586110 -7.606 8.67e-14 ***
## majority_racelatino -35802063
                                   7202575 -4.971 8.31e-07 ***
## majority_racewhite
                       93068019
                                   6825262 13.636 < 2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 56890000 on 735 degrees of freedom
## Multiple R-squared: 0.5264, Adjusted R-squared: 0.5238
## F-statistic: 204.2 on 4 and 735 DF, p-value: < 2.2e-16
```

https://stats.oarc.ucla.edu/r/dae/ordinal-logistic-regression/