# 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)
library(lmtest)
library(sandwich)
knitr::opts_chunk$set(echo = FALSE)
```

# Reading in, cleaning, and combining data

Reading in data

Cleaning main datasets

Adding redlining grade and zipcodes to purchase origination dataframe.

#### 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
    zip
     <chr>
                <dbl>
                                  <dbl>
                                                    <dbl>
                                                                       <dbl>
## 1 60614 7683047000
                                  0.791
                                                   0.0368
                                                                      0.0796
                                  0.530
                                                   0.0504
## 2 60647 5446853000
                                                                      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
```

Bar chart of total home mortgage lending to Chicago zip codes, color coding for majority race of neighborhood.

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

Creating dataframe of modern home mortgage lending by census tract used for statistical analysis.

```
## # A tibble: 3 x 11
     census_tract loan_total white_percent_avg black_percent_avg latino_percent_avg
##
     <chr>>
                       <dbl>
                                          <dbl>
                                                            <dbl>
                                                                                <dbl>
                                                                               0.0611
## 1 17031330100 1747818000
                                          0.482
                                                            0.215
## 2 17031081800 1010495000
                                                            0.0114
                                                                               0.0549
                                          0.826
## 3 17031833100
                   835049000
                                          0.606
                                                                               0.0892
                                                            0.115
## # ... 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 dataframe including redlining scores by census tract for statistical analysis.

```
## [1] 795
## [1] 742
```

### Regression 1: Simple OLS

```
##
## Call:
## lm(formula = loans_millions ~ HRS2010 + tract_pop + med_family_income +
##
       avg_loan_amount + majority_race, data = for_regression)
##
## Residuals:
##
       Min
                 1Q
                      Median
                                   3Q
                                           Max
## -285.719 -24.549
                      -2.907
                               18.785 311.622
##
## Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
##
                       7.902e+02 3.213e+02
## (Intercept)
                                              2.460 0.01413 *
## HRS2010
                       2.306e+01 3.211e+00
                                              7.180 1.71e-12 ***
                                            14.418
## tract_pop
                       1.679e-02 1.164e-03
                                                     < 2e-16 ***
                      -1.184e-02 4.139e-03
## med_family_income
                                             -2.860
                                                     0.00435 **
## avg_loan_amount
                       1.832e-04 1.384e-05
                                             13.237
                                                     < 2e-16 ***
## majority_raceblack -1.487e+01 6.374e+00
                                             -2.332 0.01995 *
## majority_racelatino -2.671e+01
                                  6.415e+00
                                             -4.163 3.51e-05 ***
## majority_racewhite
                       7.404e+01 6.172e+00 11.995 < 2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 49.82 on 734 degrees of freedom
## Multiple R-squared: 0.6664, Adjusted R-squared: 0.6632
## F-statistic: 209.5 on 7 and 734 DF, p-value: < 2.2e-16
```

```
##
## Call:
## lm(formula = loans_millions ~ redline_1930_value + tract_pop +
       med_family_income + avg_loan_amount + majority_race, data = for_regression)
##
##
## Residuals:
       Min
                 10
                      Median
                                   30
                                            Max
                      -2.334
## -284.298 -24.260
                               18.509
                                       315.055
##
## Coefficients:
##
                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                       7.996e+02 3.229e+02
                                              2.476 0.01349 *
## redline_1930_value
                       1.992e+01 3.009e+00
                                              6.620 6.91e-11 ***
                       1.656e-02
                                                    < 2e-16 ***
## tract_pop
                                 1.167e-03
                                             14.187
                                             -2.842
## med_family_income
                       -1.182e-02 4.160e-03
                                                     0.00461 **
## avg_loan_amount
                       1.840e-04
                                  1.390e-05
                                              13.237
                                                     < 2e-16 ***
                                  6.412e+00
## majority_raceblack -1.555e+01
                                             -2.425 0.01556 *
## majority_racelatino -2.683e+01
                                  6.448e+00
                                             -4.161 3.54e-05 ***
## majority_racewhite
                       7.289e+01 6.191e+00 11.773 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 50.07 on 734 degrees of freedom
## Multiple R-squared: 0.6631, Adjusted R-squared: 0.6599
## F-statistic: 206.4 on 7 and 734 DF, p-value: < 2.2e-16
```

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

Creating a new variable showing modern census tracts categorized by the same distribution as the 1930s HOLC grade for chicago.

```
##
## 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 HOLC grades. This shows us that the top census tracts by level of

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

```
##
## Call:
## lm(formula = ranking_2010 ~ value_3 + value_4, data = for_regression)
## Residuals:
##
      Min
               1Q Median
                               3Q
                                      Max
## -2.3345 -0.3141 -0.3141 0.6655 0.9000
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.10000
                          0.07528 41.180 < 2e-16 ***
                                    2.615 0.00910 **
               0.21414
                          0.08189
## value_3
## value_4
               0.23448
                          0.08387
                                    2.796 0.00531 **
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.6298 on 739 degrees of freedom
## Multiple R-squared: 0.01086,
                                   Adjusted R-squared: 0.008183
## F-statistic: 4.057 on 2 and 739 DF, p-value: 0.01769
##
## Call:
## lm(formula = ranking_2010 ~ HRS2010, data = for_regression)
## Residuals:
               1Q Median
      Min
                               3Q
                                      Max
## -2.3675 -0.2895 -0.2755 0.6374 0.8103
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.01187
                          0.12732 23.656
                                            <2e-16 ***
## HRS2010
               0.08892
                          0.03838
                                    2.316
                                            0.0208 *
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 0.6306 on 740 degrees of freedom
## Multiple R-squared: 0.007199, Adjusted R-squared: 0.005858
## F-statistic: 5.366 on 1 and 740 DF, p-value: 0.0208
```

#### Regression 3: Linear Probability Model

```
##
                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                  ## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## t test of coefficients:
##
                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                 -1.797897  0.084950 -21.164 < 2.2e-16 ***
## redline_1930_value 0.665045 0.024034 27.671 < 2.2e-16 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## t test of coefficients:
##
##
                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                  ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## t test of coefficients:
##
                  Estimate Std. Error t value Pr(>|t|)
                  ## (Intercept)
## redline_1930_value -0.359736
                         0.040676 -8.8439 < 2.2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## t test of coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
                 -1.797897 0.084950 -21.164 < 2.2e-16 ***
## (Intercept)
## redline_1930_value 0.665045
                          0.024034 27.671 < 2.2e-16 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
Regression 4: Ordered logit
## polr(formula = as.factor(ranking_2010) ~ redline_1930_value,
     data = for_regression, Hess = TRUE)
##
## Coefficients:
                  Value Std. Error t value
## redline_1930_value 0.3529
                          0.1118 3.158
##
```

```
## Intercepts:
## Value Std. Error t value
## 1|2 -4.3709 0.6779 -6.4481
## 2|3 -1.2323 0.3767 -3.2710
## 3|4 1.5949 0.3751 4.2519
##
## Residual Deviance: 1376.411
## AIC: 1384.411
```

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

# Regression summaries in stargazer for Latex

Table 1:

	Continous Redline Grade	Categorical Redline Grade
	(1)	(2)
Continous Redline Grade	23.059*** (3.211)	
Redline Categories		$19.919^{***}$ (3.009)
Tract Population	$0.017^{***} (0.001)$	$0.017^{***} (0.001)$
Average Family Income	$-0.012^{***}(0.004)$	$-0.012^{***}(0.004)$
Average Loan Amount	$0.0002^{***}$ (0.00001)	$0.0002^{***} (0.00001)$
Majority Black	$-14.866^{**}$ (6.374)	$-15.547^{**}$ (6.412)
Majority Latino	$-26.707^{***}$ (6.415)	$-26.832^{***}$ (6.448)
Majority White	74.039*** (6.172)	72.890*** (6.191)
Observations	742	742
$\mathbb{R}^2$	0.666	0.663
Adjusted R <sup>2</sup>	0.663	0.660
Residual Std. Error ( $df = 734$ )	49.821	50.068
F Statistic (df = $7$ ; $734$ )	209.468***	206.377***

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

Table 2:

	10010 2.	
	Dependent variable:  Modern Lending Ranking	
	(1)	(2)
Continous Variable	0.089** (0.038)	
Grade 3		$0.214^{***} (0.082)$
Grade 4		0.234*** (0.084)
Observations	742	742
$\mathbb{R}^2$	0.007	0.011
Adjusted R <sup>2</sup>	0.006	0.008
Residual Std. Error	0.631 (df = 740)	0.630 (df = 739)
F Statistic	$5.366^{**} (df = 1; 740)$	$4.057^{**} (df = 2; 739)$
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: Sun, May 29, 2022 - 23:17:31

Table 3:

	$Dependent\ variable:$
	ranking_2010
redline_1930_value	0.353*** (0.112)
Observations	742
Note:	*p<0.1; **p<0.05; ***p<0.05