P8130 Final Report

Amanda Tsai, Na Yun Cho, Rosemary Hahm, Ruwen Zhou, Yubei Liang

Abstract

In today's world where diversity abounds in every aspect of people's lives, hate crimes still remain a big issue that leave devastating effects on not only individuals but also communities as well. To better address and prevent future hate crimes, this study aims to identify variables that are most closely associated with hate crime rates. In doing so, we examined the data in every U.S. state that were recorded during the first weeks of November in 2016 by the Southern Poverty Law Center and examined a variety of potential factors that could be associated with hate crimes. With previous knowledge that income inequality is one of the main predictors of hate crime rates, we looked more into this factor and assessed its relationship with other variables. Through various model selections and statistical analyses, we concluded that on average, hate crime rate in the U.S. is linearly associated with an increase in the percentage of adults with a high school degree and a higher index of income inequality. The association between hate crime rate and income inequality in addition to the percentage of adults with a high school degree was stronger than that between hate crime rate and income inequality alone. Based on these results, future studies can look into identifying more factors that are closely related with hate crime rates globally and in the U.S. over the years.

Introduction

The current highest priority of the FBI's civil rights program is hate crimes. A hate crime, as defined by the FBI, is a "criminal offense against a person or property motivated in whole or in part by an offender's bias against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity."(FBI, n.d.). The number of hate crimes committed yearly in the United States has been growing and, as of 2020, has risen to the highest level in more than a decade, with 7,134 reported cases from 2019 (Balsamo, 2020). This number could be severely lower than the actual count, as hate crime data is voluntarily reported by law enforcement and only 2,172 out of the 15,000 participating agencies reported to the FBI last year (Balsamo, 2020). However, with the increasing incidence of hate crimes, there is a growing urgency to find trends within the hate crime data that can assist law enforcement agencies in addressing potentially problematic issues or provide lawmakers with justification for certain legislation and aid the detection and prevention of future incidents.

10 days after the 2016 election, more hate crimes were reported to the Southern Poverty Law Center on average per day than in the time between 2010 and 2015 (Majumder, 2017). Using the data reported in this time frame, which includes details on hate crimes that occurred in the United States by state, we seek to address the strength of association between a variety of potential variables and the incidence of hate crimes. The variables include the levels of unemployment, level of state urbanization, the median household income per state, percentage of adults over the age of 25 with high school degrees, the percentage of the population that are non-us citizens, the percentage of the population that are non-white, and the Gini index number that measures income inequality for each state (Majumder, 2017)

```
# Load libraries
rm(list = ls())
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --

## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.0.6     v dplyr   1.0.4
## v tidyr   1.1.2     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(arsenal)
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
library(boot)
```

```
# Load and tidy data, missing values of outcome variable are removed
hatecrimes_df <- read.csv("./data/HateCrimes.csv") %>%
 filter(hate_crimes_per_100k_splc != 'N/A') %>%
  mutate(
    unemployment = as.factor(unemployment),
    urbanization = as.factor(urbanization),
    hate_crime_rate = as.numeric(hate_crimes_per_100k_splc)) %>%
  select(-hate_crimes_per_100k_splc)
```

```
# Summary statistics
my_labels<-list(hate_crime_rate = "Hate Crimes(per 100k)", unemployment = "Unemplotment Level", urbaniza

#make controls
my_controls <- tableby.control(
               total = F,
               test=F,  # No test p-values yet
               numeric.stats = c("N", "meansd", "medianq1q3", "min", "max", "Nmiss2"),
               cat.stats = c("N", "countpct"),
               stats.labels = list(
                     meansd = "Mean (SD)",
                     medianq1q3 = "Median (Q1, Q3)",
                     min = "Min",
                     max = "Max",
                     Nmiss2 = "Missing",
                     countpct = "N (%)"))

#table 1
tab1<-tableby(~ hate_crime_rate + unemployment + urbanization + median_household_income + perc_populati
summary(tab1, title = "Descriptive Statistics: Hate Crimes per 100K Population and Possible Influential
```

```
##
##
## Table: Descriptive Statistics: Hate Crimes per 100K Population and Possible Influential Variables
```

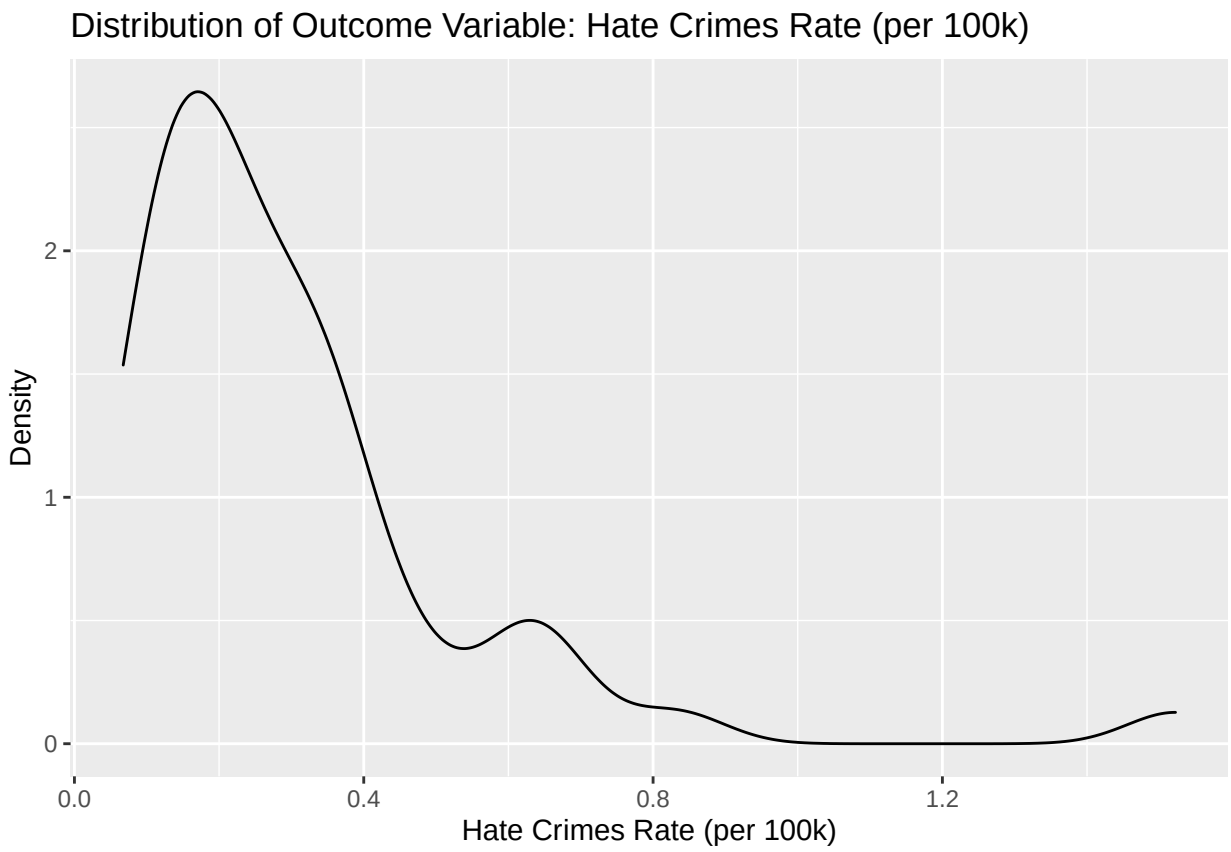
	Overall (N=47)
Hate Crimes(per 100k)	
- N	47
- Mean (SD)	0.304 (0.253)
- Median (Q1, Q3)	0.226 (0.143, 0.357)
- Min	0.067
- Max	1.522
- Missing	0
Unemplotment Level	
- N	47
- high	24 (51.1%)
- low	23 (48.9%)
Urbanization Level	
- N	47
- high	24 (51.1%)
- low	23 (48.9%)
Median Household Income(dollar)	
- N	47
- Mean (SD)	54802.298 (9255.117)
- Median (Q1, Q3)	54310.000 (47629.500, 60597.500)
- Min	35521.000
- Max	76165.000
- Missing	0
High School Degree Rate(%)	
- N	47
- Mean (SD)	0.866 (0.034)
- Median (Q1, Q3)	0.871 (0.839, 0.895)
- Min	0.799
- Max	0.915
- Missing	0
Non-Citizen Rate(%)	
- N	45
- Mean (SD)	0.055 (0.031)
- Median (Q1, Q3)	0.050 (0.030, 0.080)
- Min	0.010
- Max	0.130
- Missing	2
Non-White Rate(%)	
- N	47
- Mean (SD)	0.315 (0.150)
- Median (Q1, Q3)	0.300 (0.205, 0.420)
- Min	0.060
- Max	0.630
- Missing	0
Gini Index	
- N	47
- Mean (SD)	0.456 (0.021)
- Median (Q1, Q3)	0.455 (0.441, 0.468)
- Min	0.419
- Max	0.532
- Missing	0

Data Description

The original dataset of hate crime rate per 100k population was recorded by the Southern Poverty Law Center during the first weeks of November, 2016. Variable names include state, unemployment, urbanization, median_household_income, perc_population_with_high_school_degree, perc_non_citizen, gini_index, perc_non_white, hate_crime_rate. During the data cleaning process, 4 'N/A' observations of the outcome variable 'hate_crime_rate' were removed. Predictor variables 'unemployment' and 'urbanization' were converted to factors with levels of 'high' and 'low'. The rest of the predictor variables were numeric except 'state'. On average, 0.304 hate crime was committed per 100K population, which was as high as 1.522 in District of Columbia, the federal district. Both employment level and urbanization level were low in around half of the states and high in the rest. The median household income was 54802 dollars across the country with a standard deviation 9255. The variability of income could be addressed through the Gini Index, which had a mean value of 0.456. In other words, there is a big income gap in this country, on average. High school degree rate had a mean value of 86.6% with standard deviation of 3.4%. Moreover, Non-citizen rate had mean value of 5.5% with standard deviation of 3.1%. Lastly, non-white rate had mean value of 31.5% with standard deviation of 15%.

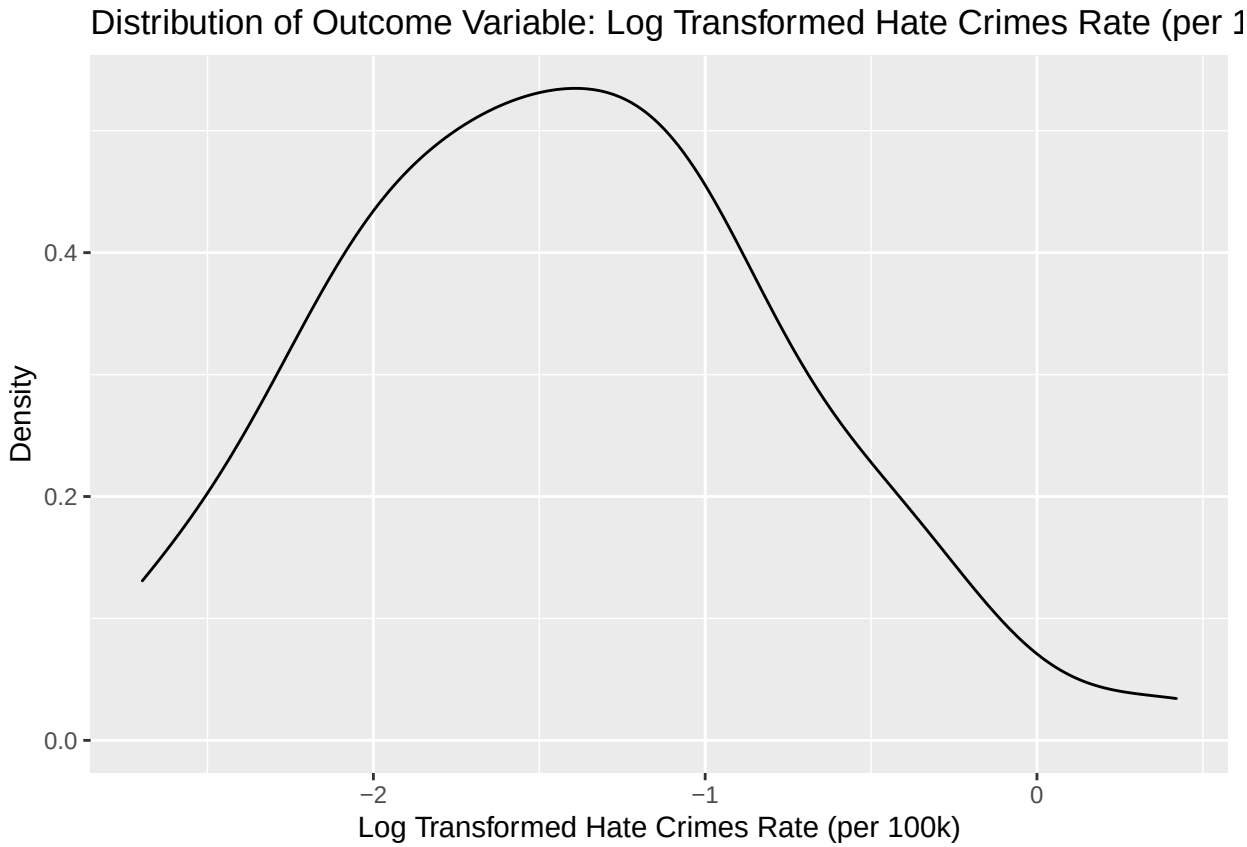
Exploratory Data Analysis

```
#Distribution of Outcome Variable
hatecrimes_df %>%
  ggplot(aes(x = hate_crime_rate)) +
  geom_density() +
  labs(x = 'Hate Crimes Rate (per 100k)', y = 'Density', title = 'Distribution of Outcome Variable: Hat
```



First, we checked the distribution of the outcome variable to detect if any transformation for normality would be needed (Figure 1). Because the distribution was highly skewed to the right, we considered doing a log transformation to the hate_crime_rate variable. The distribution of the outcome variable looked much more normal after doing a log transformation (Figure 2). We also formed a correlation matrix (Table 1), which showed a strong positive association(0.651) between perc_population_with_high_school_degree and median_household_income, and a stronger positive association(0.753) between perc_non_white and perc_non_citizen.

```
hatecrimes_df %>%
  ggplot(aes(x = log(hate_crime_rate))) +
  geom_density() +
  labs(x = 'Log Transformed Hate Crimes Rate (per 100k)', y = 'Density', title = 'Distribution of Outcor
```




```
# Correlation matrix for numeric variables
hatecrimes_df <- hatecrimes_df %>%
  drop_na()
hatecrimes_df %>%
  select(hate_crime_rate, median_household_income, perc_population_with_high_school_degree, perc_non_ci
  cor()
```

```
##                                      hate_crime_rate median_household_income
## hate_crime_rate                            1.0000000              0.34378921
## median_household_income                    0.3437892              1.00000000
## perc_population_with_high_school_degree    0.2628198              0.65113832
## perc_non_citizen                           0.2435066              0.30173941
## perc_non_white                             0.1111650              0.03905399
```

```
## gini_index                                      0.3805028             -0.12952158
##                                              perc_population_with_high_school_degree
## hate_crime_rate                                                           0.2628198
## median_household_income                                                   0.6511383
## perc_population_with_high_school_degree                                   1.0000000
## perc_non_citizen                                                         -0.2621288
## perc_non_white                                                           -0.4958932
## gini_index                                                               -0.5371591
##                                              perc_non_citizen perc_non_white
## hate_crime_rate                                     0.2435066     0.11116503
## median_household_income                             0.3017394     0.03905399
## perc_population_with_high_school_degree            -0.2621288    -0.49589321
## perc_non_citizen                                    1.0000000     0.75261020
## perc_non_white                                      0.7526102     1.00000000
## gini_index                                          0.4798976     0.54840351
##                                              gini_index
## hate_crime_rate                               0.3805028
## median_household_income                      -0.1295216
## perc_population_with_high_school_degree      -0.5371591
## perc_non_citizen                              0.4798976
## perc_non_white                                0.5484035
## gini_index                                    1.0000000
```

```
#Potential outliers/Influential points of outcome variable

# (1) Identify unusual states by using the interval formed by 2.5 and 97.5 percentiles
lower_bound <- quantile(hatecrimes_df$hate_crime_rate, 0.025)
upper_bound <- quantile(hatecrimes_df$hate_crime_rate, 0.975)

outlier <- which(hatecrimes_df$hate_crime_rate < lower_bound | hatecrimes_df$hate_crime_rate > upper_bou
hatecrimes_df[outlier, ] %>% select(state, hate_crime_rate)
```

```
##                   state hate_crime_rate
## 4              Arkansas      0.06906077
## 9  District of Columbia      1.52230172
## 28           New Jersey      0.07830591
## 34               Oregon      0.83284961
```

```
# (2) Identify unusual states by using the rule that depicts outliers (value less than Q1 - 1.5(IQR), v

hatecrimes_df %>%
  filter(hate_crime_rate > 0.678) %>%
  select(state, hate_crime_rate)
```

```
##                   state hate_crime_rate
## 1 District of Columbia       1.5223017
## 2               Oregon       0.8328496
```

```
# (3) Identify unusual states by using studentized residual, 9th row returned: District of Columbia.
fit_full <- lm(hate_crime_rate ~ gini_index + median_household_income + perc_population_with_high_schoo
stu_res<-rstandard(fit_full)
outliers_y<-stu_res[abs(stu_res)>2.5]
outliers_y
```

```
##        9
## 3.726868
```

Moreover, one of the ways we tried to identify states with unusual rates was to identify states that have the hate crime rates below the 2.5 percentile and above the 97.5 percentile. From doing so, Arkansas, District of Columbia, Mississippi, and Oregon were selected. We also identified outlier states by using the rule that depicts outliers, which are defined as values less than Q1-1.5(IQR) and values greater than Q3+1.5(IQR). From doing so, District of Columbia and Oregon were selected. Lastly, we also used the studentized residual model to identify potential outliers. This returned District of Columbia as the only outlier.