Homicide Increases in the COVID-19 Era

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Introduction

During the COVID-19 pandemic in 2021, homicide rates in Los Angeles increased substantially. A report by the Legal Defense Fund's Thurgood Marshall Institute found that this increase was associated with both pre-pandemic and pandemic-induced economic instability and inequalities.(Moore, Tom, and O'Neil 2022)

Using National Incident-Based Reporting System (NIBRS) data, this report will examine the impact of the pandemic and various socioeconomic factors on homicide rates in LA. We aim to compare the effect of these local characteristics on the incidence of homicide in pre-, mid-, and post-pandemic conditions.

We will utilize NIBRS data from 2018-2024 to examine incident-level data, allowing us to fully capture the circumstances of each event. Our data is obtained from the Los Angeles Police Department (LAPD), who regularly updates Crime Data on the Data.gov website. The data includes all crime data, which we will subset to focus on homicide, and details such as date, location, and offense type.

The codebook for this dataset can be found here: https://data.lacity.org/Public-Safety/Crime-Data-from-2020-to-Present/2nrs-mtv8/about_data.

Loading in packages and dataset

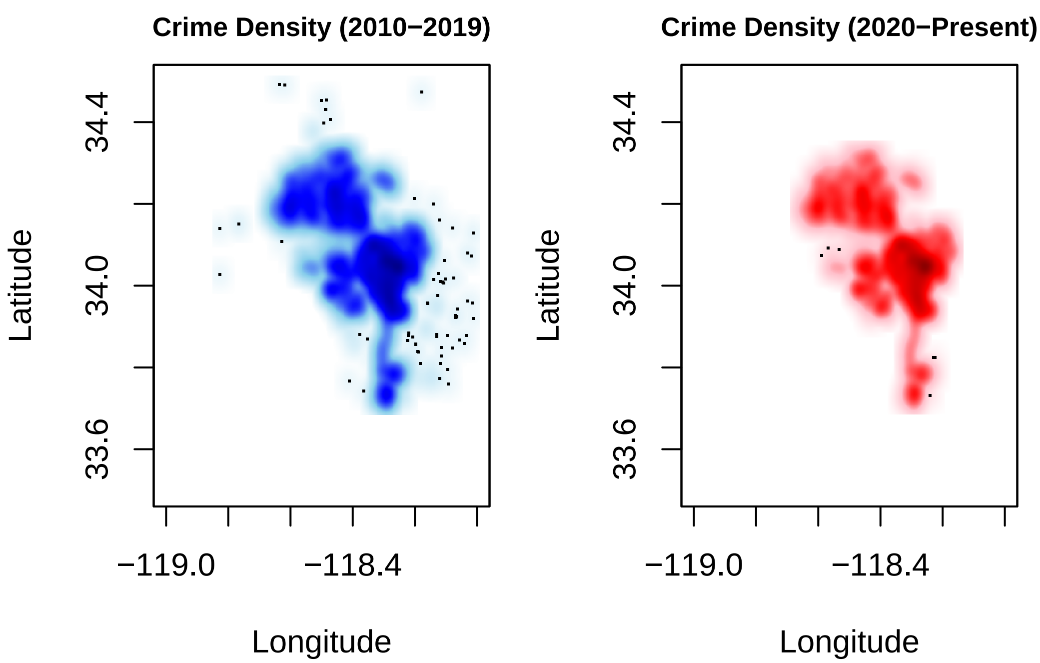
```
library(sf) # for map
library(tidyverse) # using only for joining datasets to build map visual
library(RColorBrewer) # for map color scheme
library(tidygeocoder) # to get zip codes of addresses

# Primary datasets: Crime Data 2020-Present and 2010-2019
crime_la_2010_2019 <- read.csv("Raw_Data/Crime_Data_from_2010_to_2019.csv")

crime_la_2020_present <- read.csv("Raw_Data/Crime_Data_from_2020_to_Present.csv")

# Combine the two datasets
crime_la <- rbind(crime_la_2010_2019, crime_la_2020_present)

# Secondary datasets
california_median_income_2018_2023 <- list()
yrs <- 2018:2023
for (i in 1:length(yrs)) {
  obj <- read.csv(paste0("Raw_Data/ACSST5Y",yrs[[i]],".S1903-Data.csv"), skip = 0)
  obj <- obj[-1,]
  obj$year <- yrs[[i]]
  california_median_income_2018_2023[[i]] <- obj
}

cali_median_income <- do.call(rbind, california_median_income_2018_2023)

# adding a variable that's just the ZCTA zip code
cali_median_income$ZCTA <- stringr::str_sub(cali_median_income$NAME, -5)
```

Plots

Examining Crime Density from 2010–2019 and 2020-Present

```
par(mfrow = c(1, 2), mar = c(4, 4, 2, 1))

smoothScatter(
  x    = crime_la_2010_2019$LON,
  y    = crime_la_2010_2019$LAT,
  xlim = c(-119, -118),
  ylim = c(33.5, 34.5),
  nbin = 300,
  xlab = "Longitude",
  ylab = "Latitude",
  main = "Crime Density (2010-2019)",
```

```r
  colramp = colorRampPalette(c("white", "skyblue", "blue", "darkblue")),
  cex.main=0.8
)

smoothScatter(
  x    = crime_la_2020_present$LON,
  y    = crime_la_2020_present$LAT,
  xlim = c(-119, -118),
  ylim = c(33.5, 34.5),
  nbin = 300,
  xlab = "Longitude",
  ylab = "Latitude",
  main = "Crime Density (2020-Present)",
  colramp = colorRampPalette(c("white", "pink", "red", "darkred")),
  cex.main=0.8
)
```



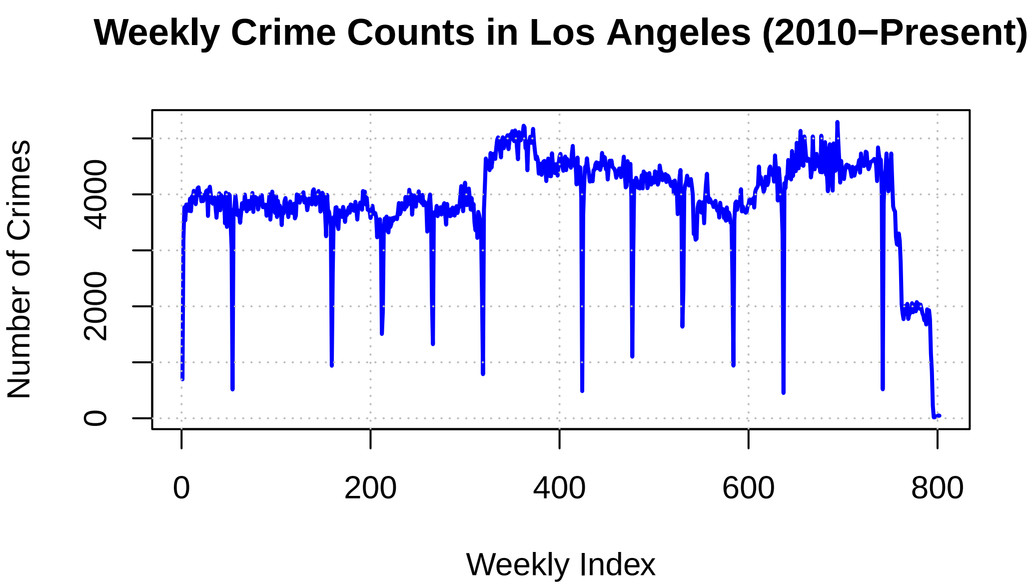

```r
par(mfrow = c(1, 1))
```

Both time periods show major clusters of reported crimes in central LA. The 2020–present data appears slightly more dispersed to the north, but overall patterns remain similar looking.

Examining Number Of Crimes Over Time

```r
crime_la$DateParsed <- as.POSIXct(crime_la$Date.Rptd,
                                  format = "%m/%d/%Y %I:%M:%S %p",
                                  tz = "America/Los_Angeles")

crime_la$YearWeek <- format(crime_la$DateParsed, "%Y-%U")
```

```
weekly_counts <- aggregate(DR_NO ~ YearWeek, data = crime_la, FUN = length)
names(weekly_counts)[2] <- "Crimes"

weekly_counts <- weekly_counts[order(weekly_counts$YearWeek), ]

weekly_counts$Index <- seq_len(nrow(weekly_counts))

plot(
  weekly_counts$Index,
  weekly_counts$Crimes,
  type = "l",
  col  = "blue",
  lwd  = 2,
  xlab = "Weekly Index",
  ylab = "Number of Crimes",
  main = "Weekly Crime Counts in Los Angeles (2010-Present)"
)

abline(h = pretty(weekly_counts$Crimes), v = pretty(weekly_counts$Index),
       col = "gray", lty = "dotted")
```



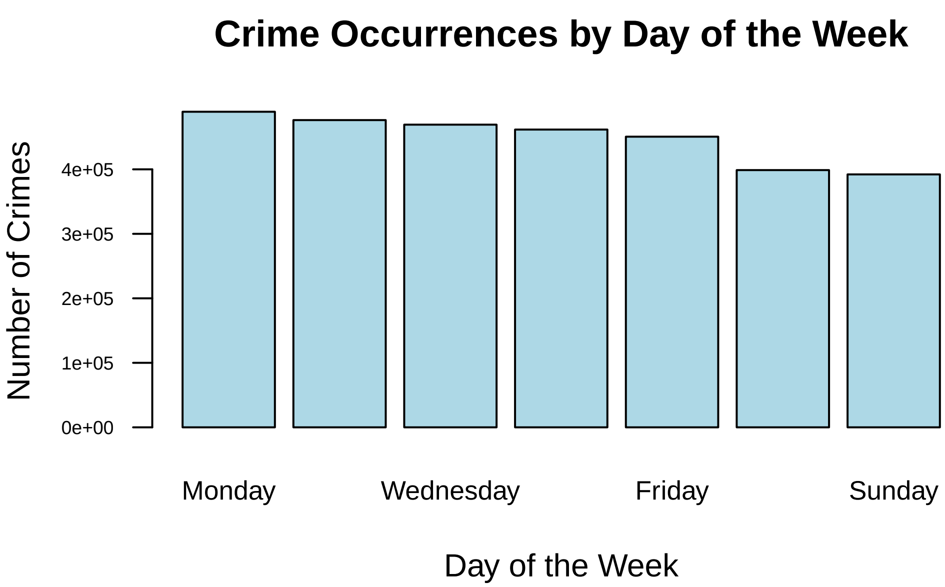
The time series shows stable weekly crime counts with occasional large spikes. These surges indicate certain weeks where crime reporting jumped significantly, there is a recent interesting surge that seems to mean-revert in 2024.

Crime rate frequency by day of the week

```
# Convert Date.Rptd to Date format (ignore time part)
#crime_la$Date.Rptd
crime_la$Date <- as.Date(substr(crime_la$Date.Rptd, 1, 10), format = "%m/%d/%Y")

# Set locale to English (for weekday names)
Sys.setlocale("LC_TIME", "C")
```

```
[1] "C"
```

```
# Extract the day of the week
crime_la$DayOfWeek <- weekdays(crime_la$Date)
# crime_la$DayOfWeek

# Count occurrences of crimes per day
crime_counts <- table(crime_la$DayOfWeek)
# crime_counts

# Order the days correctly
day_order <- c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday")
crime_counts <- crime_counts[day_order]

# Plot bar chart with horizontal labels
barplot(crime_counts, col = "lightblue",
        main = "Crime Occurrences by Day of the Week",
        xlab = "Day of the Week", ylab = "Number of Crimes",
        names.arg = names(crime_counts), las = 1, cex.names = 0.8, cex.axis = 0.6)
```

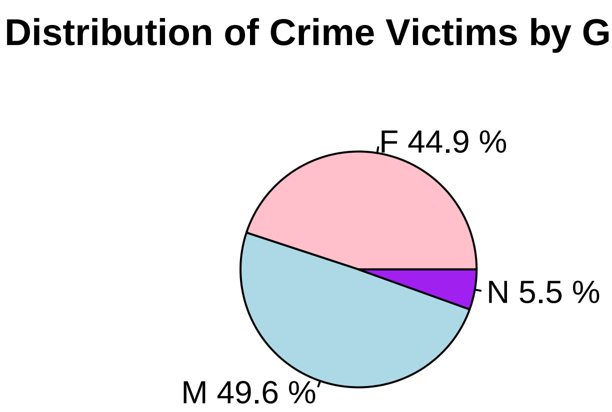


Interpretation

The number of crimes are rather evenly distributed, with the weekends having slightly lower crime compared to week days.

Gender Distribution for crimes over time

```r
# Remove missing values and empty strings in Vict.Sex column
crime_la <- subset(crime_la, Vict.Sex != "" & !is.na(Vict.Sex))

# Replace all non-"F" and non-"M" values with "N"
crime_la$Vict.Sex <- ifelse(crime_la$Vict.Sex %in% c("F", "M"),
                                  crime_la$Vict.Sex, "N")

# Count occurrences of each gender
gender_counts <- table(crime_la$Vict.Sex)

# Create a pie chart using base R
color <- c("F" = "pink", "M" = "lightblue", "N" = "purple")
pie(
  gender_counts,
  labels = paste(names(gender_counts),
                 round(gender_counts / sum(gender_counts) * 100, 1), "%"),
  col = color[names(gender_counts)],
  main = "Distribution of Crime Victims by Gender"
)
```



Interpretation

From the pie chart, we can see that around 50% of the crime is commited by male, 45% by female and 5% by non-binary.

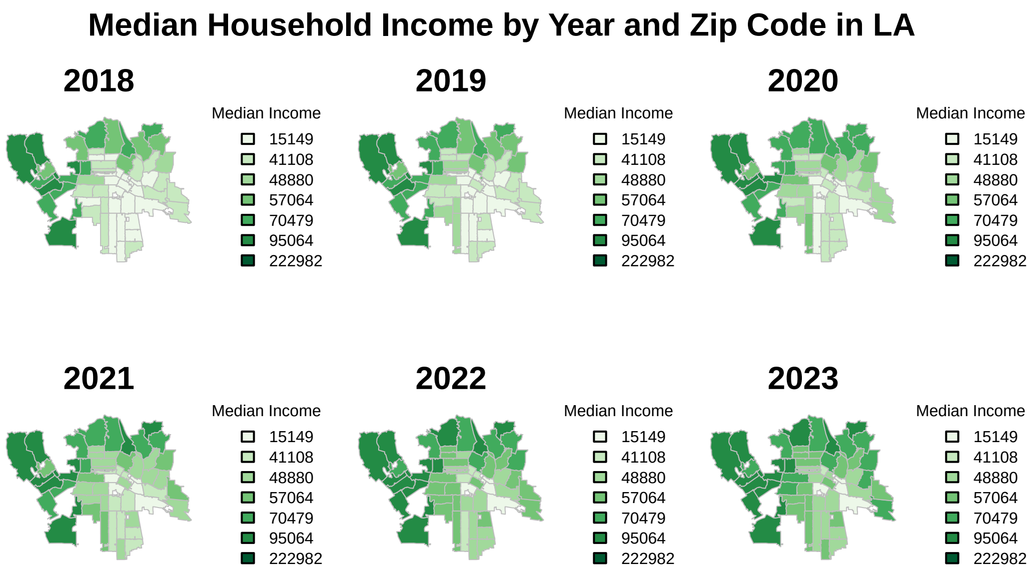
Median Household Income by Zip Code in Los Angeles by Year

```r
zcta <- read_sf(dsn = "Raw_Data/cb_2020_us_zcta520_500k", layer = "cb_2020_us_zcta520_500k")
LA_zctas <- read.csv("Raw_Data/zctas.csv") #obtained using zipcodeR::search_city("Los Angeles", "CA") ar

colnames(LA_zctas) <- c("X", "ZCTA5CE20")
LA_zctas$ZCTA5CE20 <- as.character(LA_zctas$ZCTA5CE20)

# joining the zcta shape file with LA zcta reference file
zcta_filtered <- zcta %>% inner_join(LA_zctas, by = "ZCTA5CE20")

# getting LA median income using joined file
```

```r
median_household_income <- cali_median_income %>% select(ZCTA, S1903_C03_001E, year)

zcta_with_data <- zcta_filtered %>% inner_join(median_household_income, join_by("ZCTA5CE20" == "ZCTA"))

# remove NAs
zcta_no_NAs <- zcta_with_data %>% filter(!is.na(S1903_C03_001E), S1903_C03_001E != "-")

zcta_no_NAs$S1903_C03_001E <- as.integer(zcta_no_NAs$S1903_C03_001E)
```

Now, using this joined dataset, create six maps, one for each year.

```r
# quantiles for the entire dataset (from 2018 to 2023) to divide the median income into groups
qntls <- round(quantile(zcta_no_NAs$S1903_C03_001E, probs = seq(0, 1, length.out = 7)), 0)

# 2x3 plot layout for years 2018-2023, setting margins and outer margins, main title sizes
par(mfrow = c(2, 3), mar = c(1, 1, 1, 5), oma = c(0, 0, 3, 0), cex.main = 1.5)

# color palette for sequential data
palette <- brewer.pal(7, "Greens")

yrs <- 2018:2023

for (yr in yrs) {
  # get just that year's data
  subset_data <- zcta_no_NAs[zcta_no_NAs$year == yr, ]

  # creating bins based on the qtls
  bins <- cut(subset_data$S1903_C03_001E, breaks = qntls, labels = FALSE, include.lowest = TRUE)

  # Plot
  plot(st_geometry(subset_data),
       col = palette[bins],
       border = 'grey',
       axes = FALSE,
       lwd = 0.5)
  title(yr, line = -1)

  # adding legend
  legend("right", inset = c(-.75, 0), legend = qntls, fill = palette, title = "Median Income ($)", bty =
}

# main title for all plots
mtext("Median Household Income by Year and Zip Code in LA", outer = TRUE, cex = 1, font = 2)
```



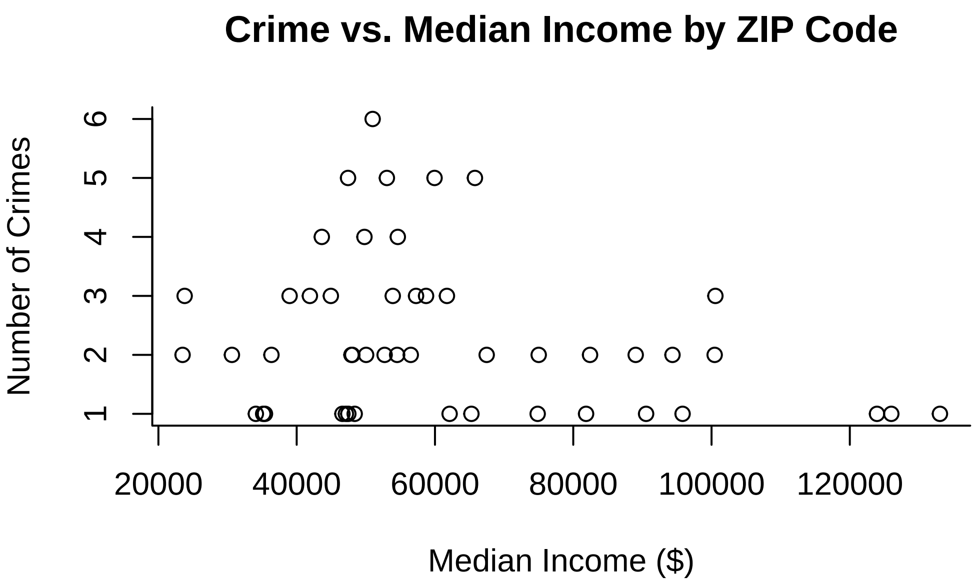
Interpretation

The maps demonstrate that median income in certain LA zip codes (particularly those to the west) have a much higher median household income than the rest of the city, but over the last six years, the median income in most other LA zip codes has increased. However, there are some that a typical family is at or below the poverty line. We intend to investigate if there is a spatial correlation between these poorer zip codes and the incidence of crimes, particularly homicide, and whether this is affected by pandemic conditions.

Crime Rates Compared to Median Household Income

```
# using latitude and longitude to obtain the zip codes of the crime locations
# crime_la$year <- as.integer(stringr::str_sub(crime_la$YearWeek, 1, 4))
# id_lat_long_crime_la <- subset(crime_la, select = c("LAT", "LON", "DR_NO", "year"))

# taking a random sample to reduce load on model
#set.seed(123)
#sampled_ids <- id_lat_long_crime_la[sample(1:nrow(id_lat_long_crime_la), 500),]
#rownames(sampled_ids) <- NULL
#zip_codes <- reverse_geocode(sampled_ids, lat = LAT, long = LON, verbose = TRUE)
#write.csv(zip_codes, "sampled_crimes.csv")
zip_codes <- read.csv("sampled_crimes.csv")

zip_codes$ZCTA5CE20 <- stringr::str_extract(zip_codes$address, "\\d{5}")

crime_income_sample <- zip_codes %>% inner_join(unique(subset(zcta_no_NAs, select = c("ZCTA5CE20", "S19

# this takes a while, so loading in this csv instead

crime_income_sample <- zip_codes %>% inner_join(unique(subset(zcta_no_NAs, select = c("ZCTA5CE20", "S19

crime_income_per_zip <- crime_income_sample %>%
  group_by(ZCTA5CE20) %>%
  summarize(number_of_crimes = n(),
```

```r
            cali_median_income = mean(S1903_C03_001E)) %>%
  ungroup()

plot(x = crime_income_per_zip$cali_median_income,
     y = crime_income_per_zip$number_of_crimes,
     type = "p",
     ylab = "Number of Crimes",
     xlab = "Median Income ($)",
     main = "Crime vs. Median Income by ZIP Code",
     bty = "l")
```



Based on this plot, we do not observe a clear trend between the number of crimes committed and the median income in that zip code. However, this scatterplot only accounts for a small portion of the dataset and averages across pre- and post-pandemic conditions. Future visualizations and analyses could consider pandemic vs non-pandemic years as variables.

Regression Analyses

Using Regression to Examine Weekly Crime Rates

```r
weekly_counts$CrimesLag <- c(NA, weekly_counts$Crimes[-nrow(weekly_counts)])

ar1_trend_regression <- lm(Crimes ~ Index + CrimesLag, data = weekly_counts, na.action = na.omit)

summary(ar1_trend_regression)
```

```
Call:
lm(formula = Crimes ~ Index + CrimesLag, data = weekly_counts,
    na.action = na.omit)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-3452.3  -137.4    13.7   150.8  3172.0 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 711.40378   86.45504   8.229 7.68e-16 ***
Index        -0.08994    0.07175  -1.254     0.21    
CrimesLag     0.82743    0.02009  41.189  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 469.2 on 798 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.6811,	Adjusted R-squared:  0.6803 
F-statistic: 852.3 on 2 and 798 DF,  p-value: < 2.2e-16
```

Interpretation

The lagged crime coefficient (0.81949) suggests that a high crime week is often followed by another high crime week. Since the trend term is not significant, there is no clear drift in weekly crime over time.

Basic Regression Between Median Income and Crimes per Zip Code

```r
lm_income_crimes <- lm(number_of_crimes ~ cali_median_income, data = crime_income_per_zip)

summary(lm_income_crimes)
```

```
Call:
lm(formula = number_of_crimes ~ cali_median_income, data = crime_income_per_zip)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.6752 -0.8829 -0.3793  0.5956  3.5464 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)         3.122e+00  4.932e-01   6.332  9.2e-08 ***
cali_median_income -1.312e-05  7.377e-06  -1.778    0.082 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.31 on 46 degrees of freedom
Multiple R-squared:  0.06432,	Adjusted R-squared:  0.04398 
F-statistic: 3.162 on 1 and 46 DF,  p-value: 0.08198
```

Interpretation

Based on the p-value, we observe that median income is not significant at a 0.05 level, meaning it does not significantly decrease the amount of crimes committed. The r^2 value additionally tells us that the income only explains a small portion of the variation in the number of crimes. As stated with the scatterplot, a larger sample and considering other factors might yield different results.

Moore, Kesha S., Ryan Tom, and Jackie O'Neil. 2022. "The Truth Behind Crime Statistics: Avoiding Distortions and Improving Public Safety." https://www.naacpldf.org/wp-content/uploads/2022-08-03-TMI-Truth-in-Crime-Statistics-Report-FINAL-2.pdf.