Homicide Increases in the COVID-19 Era

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1 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)

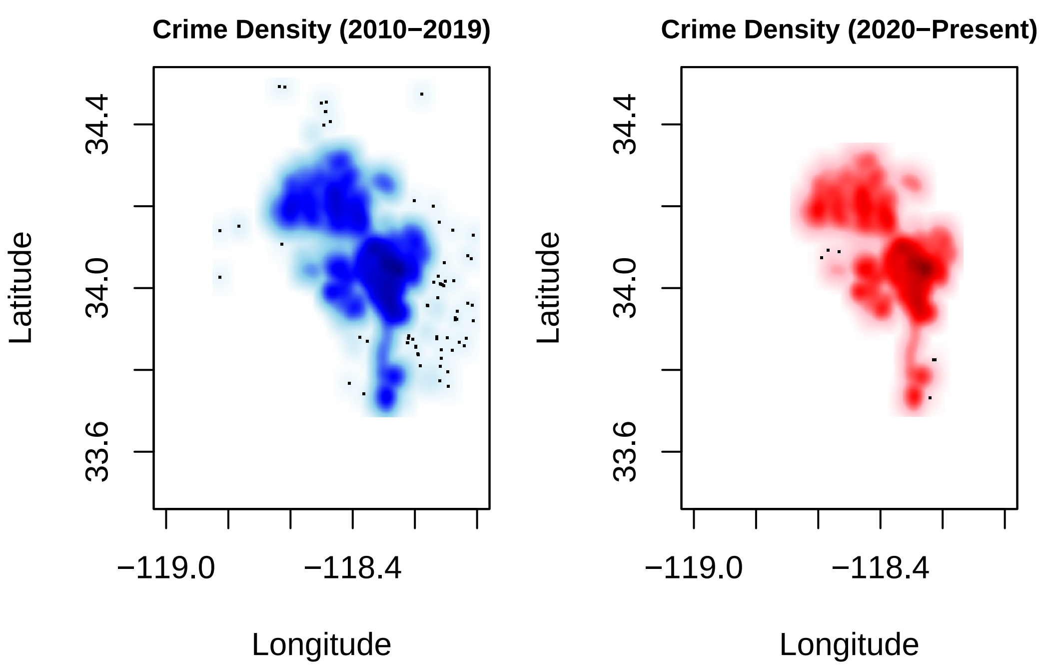
Using National Incident-Based Reporting System (NIBRS) data, this report will examine the impact of the pandemic and various socioeconomic factors on homicide rates in LA. We aim to compare the effect of these local characteristics on the incidence of homicide in pre-, mid-, and post-pandemic conditions.

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.

2 Exploratory Data Analysis

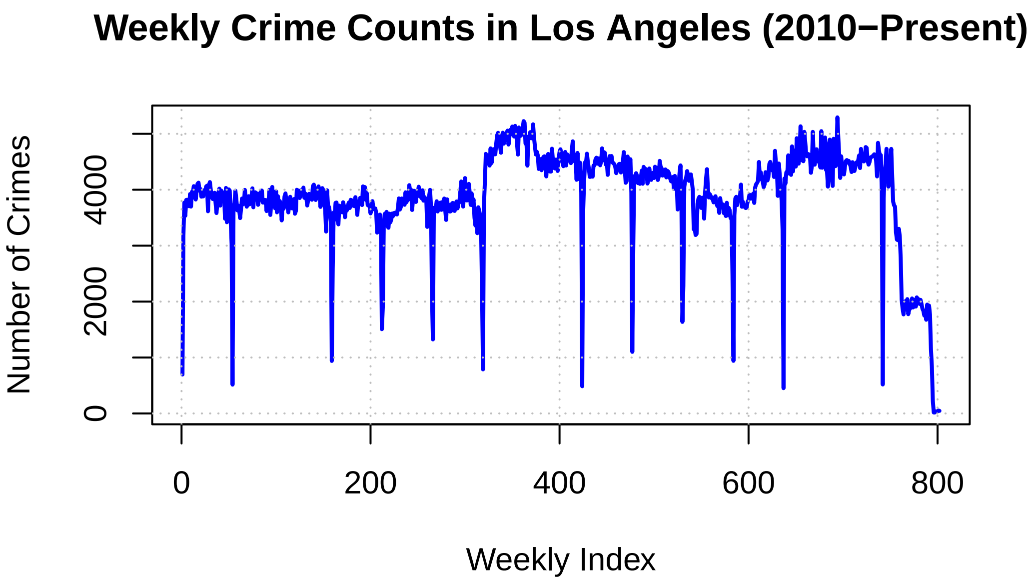
2.1 Examining Crime Density from 2010–2019 and 2020-Present



2.1.1 Interpretation

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.

2.2 Examining Number Of Crimes Over Time



2.2.1 Interpretation

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.

2.3 Crime rate frequency by day of the week

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

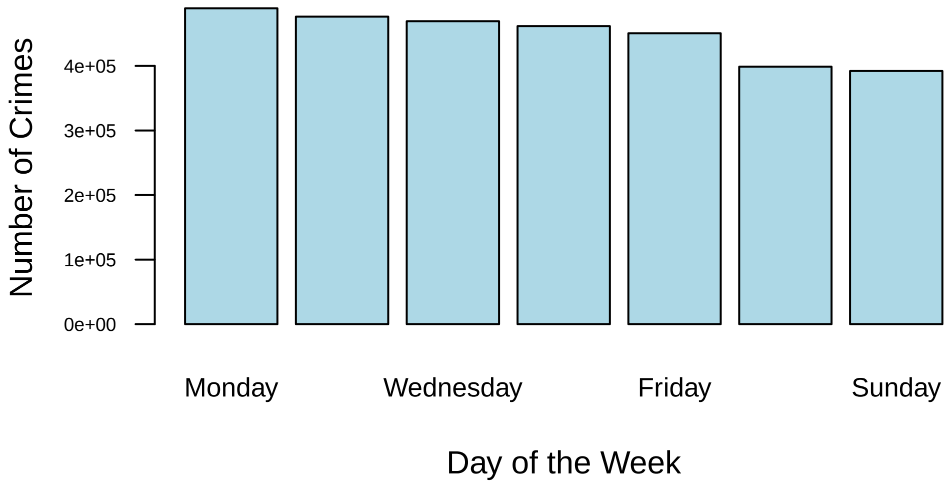
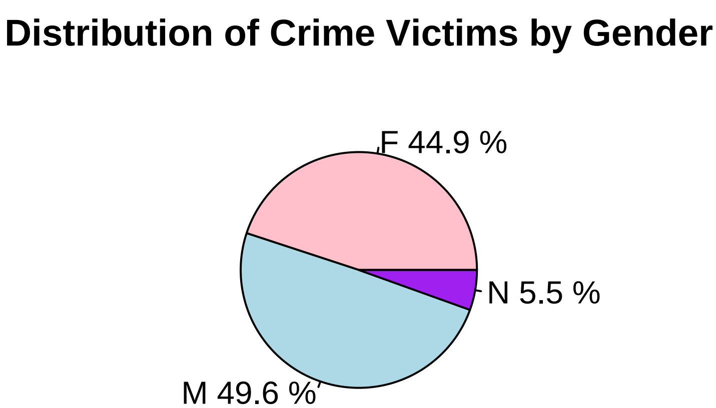


Figure 1: Crime Occurrences by Day of the Week

2.3.1 Interpretation

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

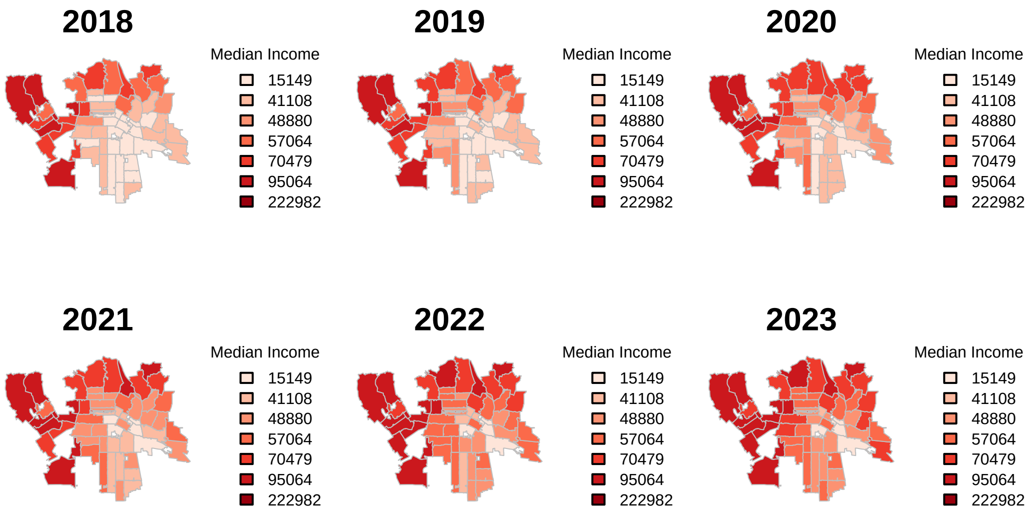
2.4 Gender Distribution for crimes over time



2.4.1 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.

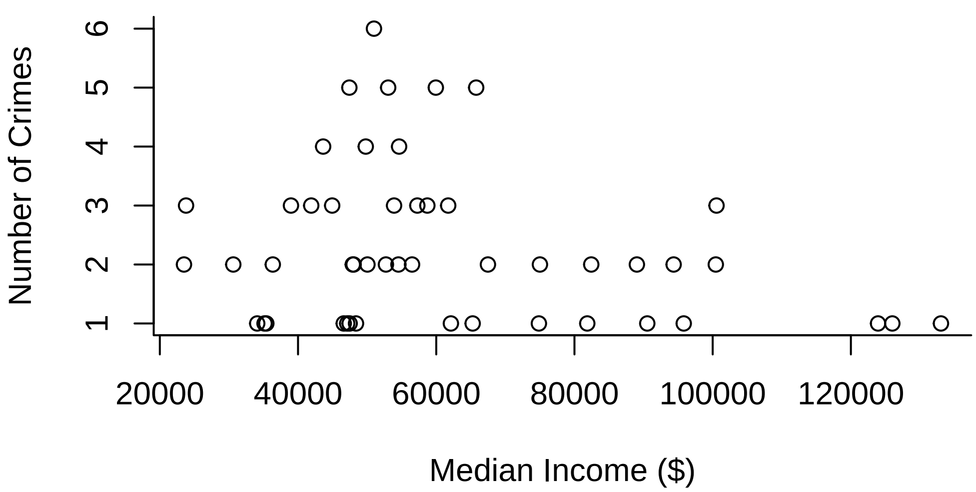
2.5 Median Household Income by Year and Zip Code in Los Angeles



2.5.1 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.

2.6 Crime Rates Compared to Median Household Income

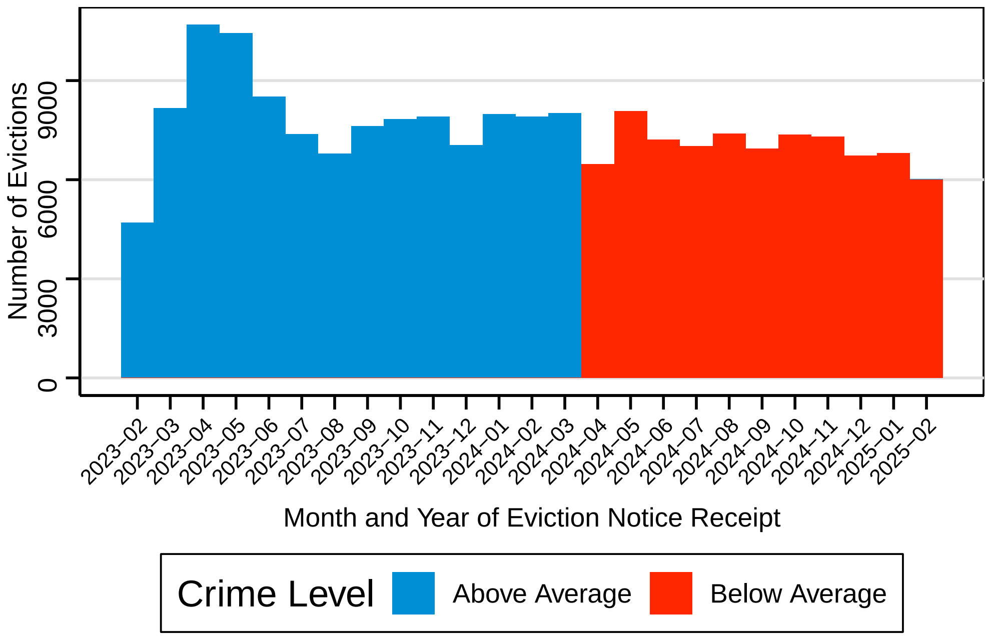


2.6.1 Interpretation

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.

3 Exploratory Data Analysis With ggplot2

3.1 Monthly Frequency of Evictions and Crimes in the City of Los Angeles, February 2023 to February 2025

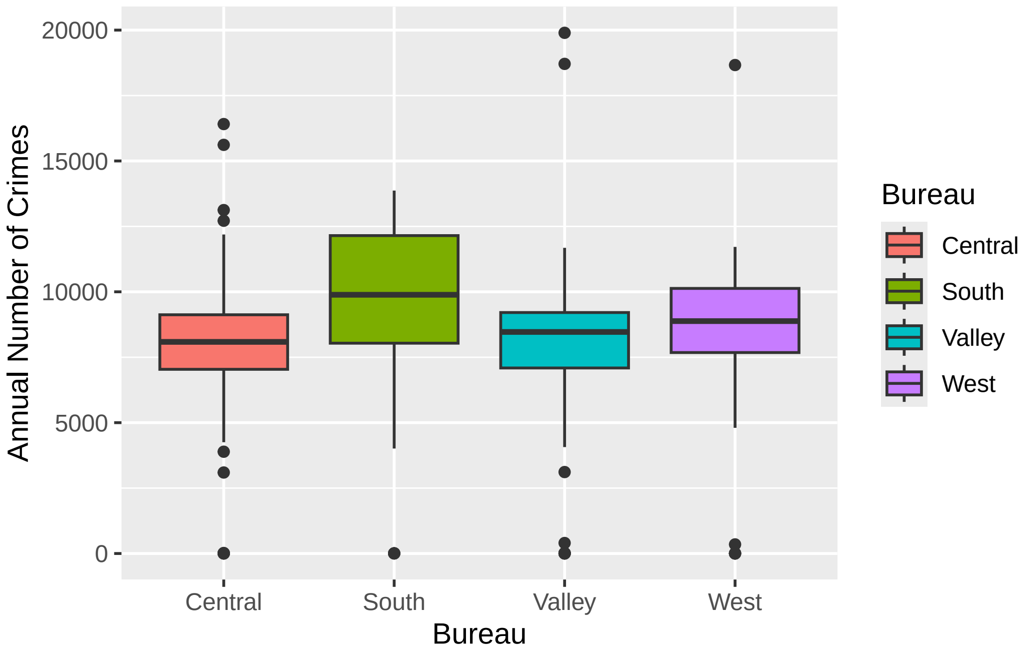


3.1.1 Interpretation

This histogram plots the frequency of evictions in Los Angeles from February 2023 to February 2025, where the City of Los Angeles Housing Department has published case data. By summarizing both the crime and the evictions datasets by month, we see that the number of evictions was highest in early-mid 2023, and since, there have typically been slightly lower frequencies of evictions. Additionally, we split the number of crimes per month based on the average number of crimes of 14,439 to denote above and below average number of crimes per month. There is a clear split between March and April of 2024, as all months before that had above average crime, and all after had below average. Interestingly, the months where there is below average crime, seem to be the ones with slightly lower numbers of evictions.

3.2 Annual Number of Crimes by Los Angeles Police Department Bureau

```
`summarise()` has grouped output by 'AREA.NAME'. You can override using the
`.groups` argument.
```

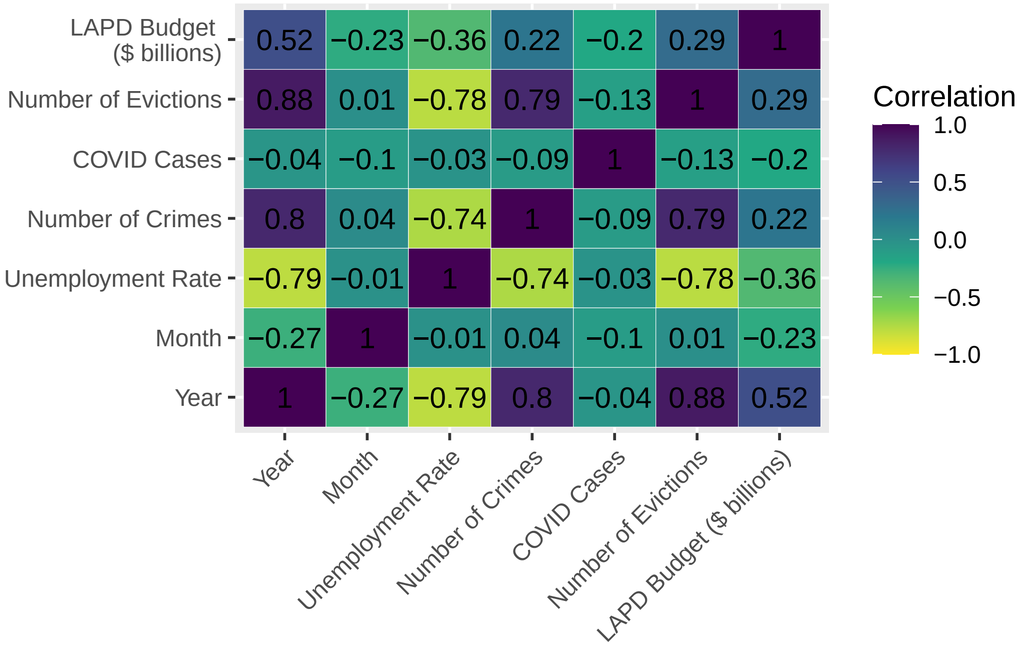


3.2.1 Interpretation

This boxplot shows the number of crimes in the four different bureaus of Los Angeles annually. We categorized the areas into their respective Central, South, Valley, and West Bureaus. The South Bureau has the highest median number of crimes, as well as the largest variability, while the Central, Valley, and West bureaus have relatively similar distributions with lower crime counts.The outliers suggests some years had significantly lower crime counts than others. This visualization helps us understand how crime is distributed across different regions, with the South experiencing the highest fluctuation and overall crime levels.

3.3 Correlations Between the Number of Crimes and Different Law Enforcement and Socioeconomic Factors

```
`summarise()` has grouped output by 'month'. You can override using the
`.groups` argument.
```

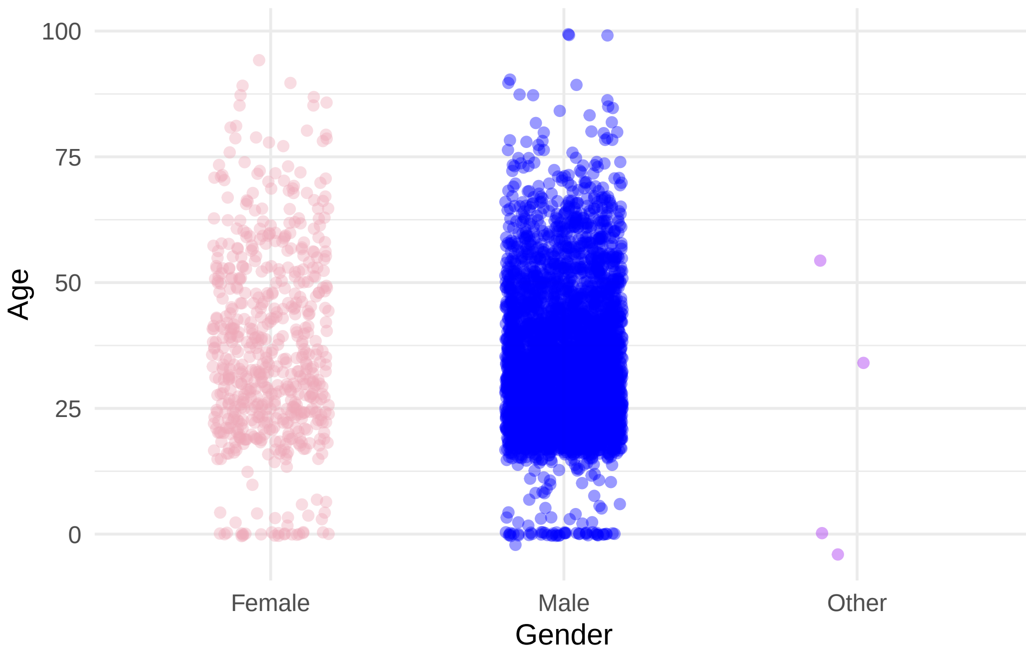


3.3.1 Interpretation

This heat map shows the correlations between different variables that could affect the number of crimes committed. Due to difficulties in obtaining city-level data, the unemployment rate, COVID cases, and number of evictions are for Los Angeles County, while the crime data is for the City of Los Angeles. The city comprises about a third of the county's population and the greater county area largely reflects the trends in the city itself.

Here, we see that the most significant correlations for the number of crimes are the unemployment rate, year, and number of evictions. Years is positively correlated with number of crimes, meaning that as time passed, the number of crimes increased. Similarly, as the number of evictions increases, so does the number of crimes. Interestingly, as the unemployment rate increases, the number of crimes decreases, which is the opposite effect of what was expected (one would anticipate that higher unemployment would result in more crime). The LAPD budget interestingly had a medium-strength positive correlation with number of crimes, suggesting we should further examine the increase in the LAPD budget compared to the increase in crimes.

3.4 Homicide Victims by Age and Gender in Los Angeles 2010-Present

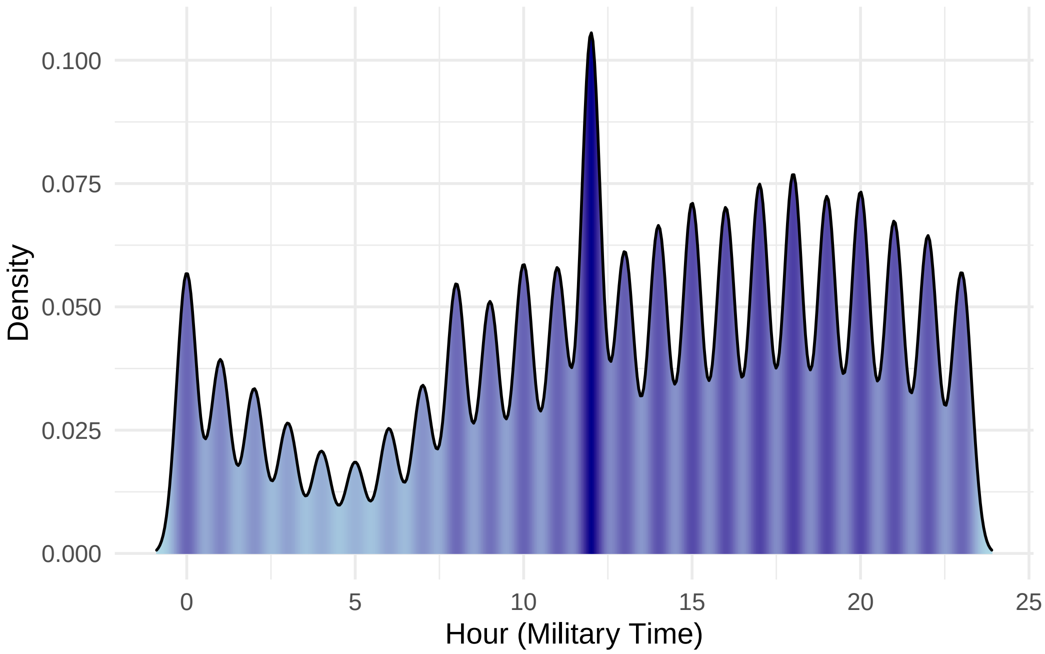


3.4.1 Interpretation

This jitter plot shows us both the frequencies and the demographics of homicide victims in Los Angeles from 2010 to present. Based on the density of the points, we see that most homicide victims in the last 15 years have been men between the ages of around 15 to 65. Additionally, we see that there are not many victims who are toddlers and younger children, but there is a good number of babies who have been killed. This is an intricacy in our data that might be interesting to look into further, particularly into the circumstances of those deaths and potential correlations between reports of child abuse and/or domestic violence and infanticide.

3.5 Frequency of Crimes in Los Angeles Throughout the Day

```
Picking joint bandwidth of 0.299
```

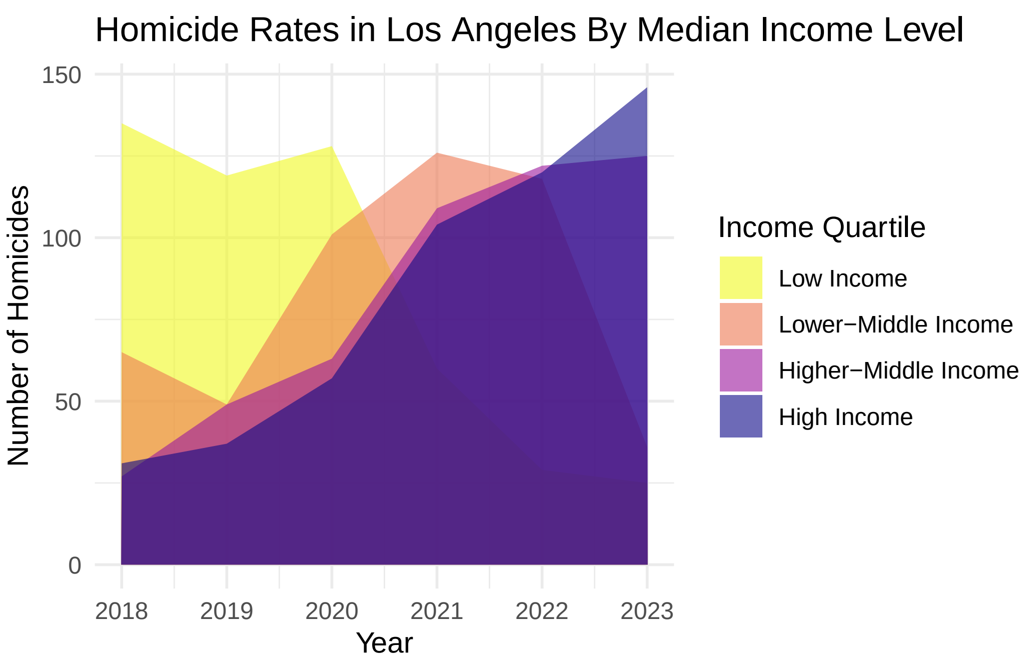


3.5.1 Interpretation

This density plot shows the frequency of crimes depending on the hour (in military time) that they occurred. Based on the plot, we see that fewer crimes occur early in the morning (with the lowest at 5 AM). The data peaks at noon, meaning the most crimes occur in that hour of the day. Crimes are more frequent after that, until the early morning. The second most common crime occurrence is 6 PM, or 18 hours.

3.6 Time series analyzing homicide rate trends over time by socioeconomic quartiles

```
Warning: NAs introduced by coercion
```



3.6.1 Interpretation

Homicide rates were low pre-pandemic and had a sharp increase since the pandemic, except in areas of low income, where homicide rates were high before the pandemic. In lower income areas, the rates of homicide have decreased significantly since the end of the pandemic. On the other hand, areas of higher-middle and high income have seen large increases in homicide in the six years shown.

4 Regression Analyses

4.1 Regression to Examine Weekly Crime Rates

Table 1: Linear Regression Model Results Estimating Crimes Per Week

Predictor	B	SE	t	p
(Intercept)	711.40	86.455	8.23	<0.001
Index	-0.09	0.072	-1.25	0.210
CrimesLag	0.83	0.020	41.19	<0.001

4.1.1 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.

4.2 Regression Between Median Income and Crimes per Zip Code

Table 2: Linear Regression Model Results Estimating Crimes Based on Median Income

Predictor	B	SE	t	p
(Intercept)	3.12	0.493	6.33	<0.001
cali_median_income	0.00	0.000	-1.78	0.082

4.2.1 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.

References

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.

Data Sources

Primary Datasets

Crime Data From 2010-2019: https://data.lacity.org/Public-Safety/Crime-Data-from-2010-to-2019/63jg-8b9z/about_data

Crime Data From 2020-Present: https://catalog.data.gov/dataset/crime-data-from-2020-to-present

Secondary Datasets

Los Angeles County Eviction Data: https://calmatters.org/housing/homelessness/2023/11/california-evictions-post-pandemic/

City of Los Angeles Eviction Data: https://housing.lacity.gov/residents/renters/eviction-notices-filed

Median Income Data: https://data.census.gov/table/ACSST1Y2023.S1903?q=income

5 Appendices

Data Wrangling

5.0.0.0.1 Reading in Raw Datasets

```r
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("0_Data/Raw_Data/Crime_Data_from_2010_to_2019.csv")

crime_la_2020_present <- read.csv("0_Data/Raw_Data/Crime_Data_from_2020_to_Present.csv")

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

```r
# Secondary datasets
california_median_income_2018_2023 <- list()
yrs <- 2018:2023
for (i in 1:length(yrs)) {
  obj <- read.csv(paste0("0_Data/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)
```

```r
write.csv(cali_median_income, "cali_median_income.csv")
```

5.0.0.0.2 Zip Codes for Crimes

```r
library(sf)
library(dplyr)

crime_la_2010_2019 <- read.csv("0_Data/Raw_Data/Crime_Data_from_2010_to_2019.csv")

crime_la_2020_present <- read.csv("0_Data/Raw_Data/Crime_Data_from_2020_to_Present.csv")

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

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")

crime_la$year <- as.integer(stringr::str_sub(crime_la$YearWeek, 1, 4))

coords <- crime_la %>% select(LAT, LON, DR_NO, year)

zcta <- read_sf(dsn = "0_Data/Raw_Data/cb_2020_us_zcta520_500k", layer = "cb_2020_us_zcta520_500k")

  points <- st_as_sf(coords, coords = c("LON", "LAT"), crs = 4326)  # WGS84

  zcta <- st_transform(zcta, 4326)  # Convert ZCTA to WGS84 if needed
  cat("Starting Zip Code Retrieval \n")

  result <- st_join(points, zcta)

  cat("Finished Zip Code Retrieval \n")

  write.csv(result, "0_Data/Raw_Data/all_zips.csv")

crime_zctas <- read.csv("0_Data/Raw_Data/all_zips.csv")
colnames(crime_zctas) <- c(colnames(crime_zctas)[-c(1, length(colnames(crime_zctas)))],"LON", "LAT")

crime_zctas$LON <- as.numeric(gsub('c(', "", crime_zctas$LON, fixed = TRUE))
crime_zctas$LAT <- as.numeric(gsub(')', "", crime_zctas$LAT, fixed = TRUE))
```

```r
duplicates <- as.integer(as.character(data.frame(table(crime_zctas$universal_idx)[table(crime_zctas$uni

# there are approximately 200 rows that are duplicated (100 incidents) as the area lies on the intersec
duplicate_data <- crime_zctas %>% filter(universal_idx %in% duplicates)

rev_geo_duplicates <- reverse_geocode(duplicates2, lat = LAT, long = LON)
# the above query identifies the address of these coordinates as KFC, 8644, Balboa Boulevard, Northridg
# therefore, we will only keep the 91325 zip code rows.
```

```r
crime_zctas_no_duplicates <- crime_zctas %>% mutate(duplicate = ifelse(universal_idx %in% duplicate_data

# it's empty now
# duplicates <- table(crime_zctas_no_duplicates$universal_idx)[table(crime_zctas_no_duplicates$universal

# next, check for NAs
sum(is.na(crime_zctas_no_duplicates$ZCTA5CE20)) # there are 3724 NAs. Let's find them a zip code

# some also have lat long = 0. We'll find those separately
no_zipcode_not0 <- crime_zctas_no_duplicates %>% filter(is.na(ZCTA5CE20) & LON != 0)

no_zipcode_not0_zips <- reverse_geocode(no_zipcode_not0, lat = LAT, long = LON)

no_zipcode_not0_zips$ZCTA5CE20 <- stringr::str_extract(no_zipcode_not0_zips$address, "\\d{5}")

no_zipcode_not0_zips <- no_zipcode_not0_zips %>% select(-address)

crime_zctas2 <- crime_zctas_no_duplicates %>% filter(!is.na(ZCTA5CE20))

crime_zctas3 <- rbind(crime_zctas2, no_zipcode_not0_zips)

crime_zctas4 <- crime_zctas3 %>% filter(!is.na(ZCTA5CE20))

write.csv(crime_zctas4, "crimes_with_zips.csv")

no_zipcode_0s <- crime_zctas_no_duplicates %>% filter(is.na(ZCTA5CE20) & LON == 0) %>% pull(DR_NO)

main_dataset_0s <- crime_la %>% filter(DR_NO %in% no_zipcode_0s)

summary(main_dataset_0s)

summary(crime_la)
```

Figure 1 - Examining Crime Density from 2010–2019 and 2020-Present

```r
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)",
  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
)

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

Figure 2 - Examining Number Of Crimes Over Time

```
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")
```

Figure 3 - 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")
```

```
# 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",
        xlab = "Day of the Week", ylab = "Number of Crimes",
        names.arg = names(crime_counts), las = 1, cex.names = 0.8, cex.axis = 0.6)
```

Figure 4 - Gender Distribution for crimes over time

```
# 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"
)
```

Figure 5 - Median Household Income by Zip Code in Los Angeles by Year

```
zcta <- read_sf(dsn = "0_Data/Raw_Data/cb_2020_us_zcta520_500k", layer = "cb_2020_us_zcta520_500k")
LA_zctas <- read.csv("0_Data/Raw_Data/zctas.csv") #obtained using zipcodeR::search_city("Los Angeles",

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

```r
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)
```

```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)
```

Figure 6 - Crime Rates Compared to Median Household Income

```r
# 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")
```

```r
zip_codes <- read.csv("0_Data/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", "S190

# 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", "S190

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

####Figure 7 - Monthly Frequency of Evictions and Crimes in the City of Los Angeles, February 2023 to February 2025 {.unnumbered}

```r
# fix mistake
evictions_la$Date.Received <- gsub("2205", "2025", evictions_la$Date.Received)

# convert to date
evictions_la$month_year <- format(as.Date(evictions_la$Date.Received, format="%m-%d-%Y"), "%Y-%m")

# get unique months
unique_months <- data.frame(month_year = sort(unique(evictions_la$month_year)), index = 1:length(unique

evictions_la_indexed <- evictions_la %>% left_join(unique_months, by = "month_year")

# create color scheme
crime_la$month_year <- format(crime_la$DateParsed, "%Y-%m")
crime_la_monthly <- crime_la %>%
  group_by(month_year) %>%
  summarize(num_crimes = n())

evictions_la_indexed_crimes <- evictions_la_indexed %>% left_join(crime_la_monthly, by = "month_year")

avg_crimes <- mean(evictions_la_indexed_crimes$num_crimes)

evictions_la_indexed_crimes$high_low_crime <- as.factor(ifelse(evictions_la_indexed_crimes$num_crimes >


ggplot(data = evictions_la_indexed_crimes, aes(x = index)) +
  geom_histogram(aes(fill = high_low_crime), bins = nrow(unique_months)) +
```

```r
  scale_x_continuous(breaks=unique_months$index,
        labels=unique_months$month_year) +
  labs(x = "Month and Year of Eviction Notice Receipt", y = "Number of Evictions", fill = "Crime Level")
  ggthemes::scale_fill_fivethirtyeight() +
  ggthemes::theme_stata(scheme = "s1mono") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8),
        axis.title.x = element_text(vjust = -.75),
        plot.title = element_text(size=12))
```

Figure 8 - Annual Number of Crimes by Los Angeles Police Department Bureau

```r
crime_la$year <- lubridate::year(crime_la$DateParsed)
crime_by_area <- crime_la %>% group_by(AREA.NAME, year) %>% summarize(numberOfCrimes = n()) %>% ungroup

bureaus <- read.csv("0_Data/Raw_Data/Division_Bureau_Ref.csv")

bureaus$Division <- gsub("77th", "77th Street", bureaus$Division)
bureaus$Division <- gsub("North", "N", bureaus$Division)
bureaus$Division <- gsub("Neast", "Northeast", bureaus$Division)

crime_by_area <- crime_by_area %>% left_join(bureaus, join_by("AREA.NAME" == "Division"))

ggplot(crime_by_area, aes(y = numberOfCrimes, group = Bureau, x = Bureau)) +
        geom_boxplot(aes(fill = Bureau)) +
  labs(y = "Annual Number of Crimes")
```

Figure 9 - Correlations Between the Number of Crimes and Different Law Enforcement and Socioeconomic Factors

```r
library(lubridate)
# creating dataset for correlations

# since we do not have pre- and post- pandemic city of LA data, we are instead using LA county data for
LA_county_evictions <- read.csv("0_Data/Raw_Data/LA_county_evictions.csv")

# covid data
covid_14day$date <- ymd(covid_14day$ep_date)
covid_14day$month <- month(covid_14day$date)
covid_14day$year <- year(covid_14day$date)
covid_14day$date <- day(covid_14day$date)
# since there is a 7 day lag in reporting, let's do monthly = cases on the 21st and on the 5th of the ne
covid_14day$lagged <- covid_14day$date + 7

covid_la_lagged <- covid_14day %>% filter(lagged %in% c(21, 35)) %>% arrange(month, year)

covid_la_monthly <- covid_la_lagged %>% group_by(month, year) %>% summarize(cases = sum(cases_14day)) %

covid_la_monthly$index <- 1:nrow(covid_la_monthly)

# next, unemployment rate
unemployment <- read.csv("0_Data/Raw_Data/la_county_unemployment_rate.csv")
```

```
unemployment$month <- as.numeric(gsub("M", "", unemployment$Period))

# lapd budget
lapd_budget <- read.csv("0_Data/Raw_Data/lapd_budget.csv")

crime_la_monthly$date <- ymd(paste0(crime_la_monthly$month_year, "-01"))
crime_la_monthly$month <- month(crime_la_monthly$date)
crime_la_monthly$year <- year(crime_la_monthly$date)

correlations_df <- crime_la_monthly %>% inner_join(unemployment, join_by("year" == "Year", "month" == "r

correlations_df2 <- correlations_df %>% inner_join(covid_la_monthly, by = c("month", "year"))

correlations_df3 <- correlations_df2 %>% inner_join(LA_county_evictions, join_by("year" == "Year", "mon

correlations_df4 <- correlations_df3 %>% inner_join(lapd_budget, by = "year")

correlations <- correlations_df4 %>% select(year, month, unemployment_rate, num_crimes, cases, num_evic

Cor_mat <- round(cor(correlations), 2)

long_Cor <- reshape2::melt(Cor_mat)

long_Cor <- long_Cor %>%
    mutate(Var1 = recode(Var1, year = 'Year', month = 'Month', unemployment_rate =  'Unemployment Rate'
           Var2 = recode(Var2, year = 'Year', month = 'Month', unemployment_rate =  'Unemployment Rate'

ggplot(data = long_Cor, aes(x = Var1, y = Var2, fill = value)) +
  geom_tile(color = "white") +
  scale_fill_viridis_c(direction = -1,limit = c(-1, 1)) +
  theme(axis.title.x =  element_blank(),
        axis.title.y = element_blank()) +
  geom_text(aes(label = value), color = "black", size = 4) +
   theme(axis.text.x = element_text(angle = 45, hjust = 1),
        plot.title = element_text(size=12)) +
  labs(fill = "Correlation")
```

Figure 10 - Homicide Victims by Age and Gender in Los Angeles 2010-Present

```
homicide_by_gender <- crime_la %>% filter(Crm.Cd.Desc == "CRIMINAL HOMICIDE") %>% select(Vict.Sex, Date

levels(homicide_by_gender$gender) <- c("Female", "Male", "Other")
ggplot(homicide_by_gender, aes(x = gender, y = Vict.Age, color = gender)) +
  geom_jitter(alpha = 0.4, width = 0.2) +
  labs(x = "Gender",
       y = "Age") +
  theme_minimal() +
  scale_color_manual(c("M", "F", "N"), values = c("pink2", "blue", "purple")) +
  theme(legend.position = 'none')
```

Figure 11 - Frequency of Crimes in Los Angeles Throughout the Day

```
crime_la$time <- sprintf("%04d",crime_la$TIME.OCC)
crime_la$Hour <- as.numeric(substr(as.character(crime_la$time), start = 1, stop = 2))

ggplot(crime_la, aes(x = Hour, y = 0, fill = after_stat(density))) +
  ggridges::geom_density_ridges_gradient(scale = 1, alpha = 0.5) +
  scale_fill_gradient(low = "lightblue", high = "darkblue") +
  labs(x = "Hour (Military Time)",
       y = "Density") +
  theme_minimal() +
  theme(legend.position = 'none')
```

Figure 12 - Time series analyzing homicide rate trends over time by socioeconomic quartiles

```
# Data Preparation
homicides <- crime_la %>% inner_join(crimes_with_zips, by = c("DR_NO", "LAT", "LON","X", "year")) %>% f
  mutate(date = as.Date(DateParsed),
         zip = as.character(ZCTA5CE20)) %>% select(-X)

homicides <- homicides %>% inner_join(cali_median_income, join_by("zip" == "ZCTA", "year" == "year"))
homicides$S1903_C03_001E <- as.numeric(homicides$S1903_C03_001E)

# Form income quartiles
homicides <- homicides %>% mutate(income_quartile = ntile(S1903_C03_001E, 4))
homicide_trends <- homicides %>% group_by(year, income_quartile) %>% summarize(homicide_count = n(),
          ref = mean(S1903_C03_001E),
          .groups = "drop")

homicide_trends$income_quartile <- as.factor(homicide_trends$income_quartile)
# removing NAs
homicide_trends <- homicide_trends %>% filter(!is.na(homicide_count) & !is.na(income_quartile))

# creating labels
levels(homicide_trends$income_quartile) <- c("Low Income", "Lower-Middle Income", "Higher-Middle Income
# Plot homicide trends over time by income quartile
ggplot(homicide_trends, aes(x = year, y = homicide_count)) +
  geom_area(aes(fill = as.factor(income_quartile)), alpha = 0.6, position = "identity") +
  labs(
    x = "Year",
    y = "Number of Homicides",
    fill = "Income Quartile",
    title = "Homicide Rates in Los Angeles By Median Income Level"
  ) +
  theme_minimal() +
  scale_fill_viridis_d(option = "plasma", direction = -1)
```

Crime ~ Week Regression Code

```
library(broom)

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

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

ar1_trend_regression %>%
tidy() %>%
  mutate(
    p.value = scales::pvalue(p.value)
  ) %>%
  knitr::kable(
    caption = "Linear Regression Model Results Estimating Crimes Per Week",
    col.names = c("Predictor", "B", "SE", "t", "p"),
    digits = c(0, 2, 3, 2, 3),
    align = c("l", "r", "r", "r", "r")
  )
```

Crime ~ Income Regression Code

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

summary(lm_income_crimes)

lm_income_crimes %>%
tidy() %>%
  mutate(
    p.value = scales::pvalue(p.value)
  ) %>%
  knitr::kable(
    caption = "Linear Regression Model Results Estimating Crimes Based on Median Income",
    col.names = c("Predictor", "B", "SE", "t", "p"),
    digits = c(0, 2, 3, 2, 3),
    align = c("l", "r", "r", "r", "r")
  )
```