# Problemset5

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11/04/2020

**Abstract**

The objective of this analysis was to examine if there was a relationship between [...]

## Introduction (Sharon)

Canadian context

https://www.sciencedaily.com/releases/2016/08/160831102834.htm

High-alcohol usage crimes (reference study)

https://www-degruyter-com.myaccess.library.utoronto.ca/view/journals/bejeap/14/3/article-p791.xml

## Research Question & Hypotheses

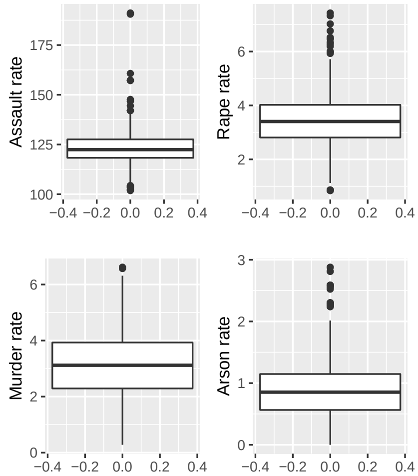
This study intend to confirm [...]

## Dataset Description and Data Cleaning

The dataset is the replication data of The Minimum Legal Drinking Age and Crime by Christopher Carpenter and Carlos Dobkin (2015). The dataset contains 1461 observations and 144 variables. The observation is arrestee's age in days relative to 21 on the day being arrested ranging from 17 to 24. For example, 30 indicates that the arrestee is a month away from turning 21, 60 indicates that the arrestee is 21 and two months old and 0 means the arrestee is arrested on their 21st birthday. The crimes data retrieved from California's Monthly Arrest and Citation Register dated from 1979 to 2006, containing major crime types categorized by FBI: violent crime, alcohol-related offenses, property crime, illegal drug possession or sale, and all other offenses. The dataset contains the counts of arrests as well the arrest rates per 10,000 person-years for each crime for each observation.

An additional variable over_21 is created

The distribution and descriptive statistics of the High-alcohol usage crimes is shown in Figure 1.




| stats | days_to_21 | mlda_and_over | assault | rape | murder | arson |
|---|---|---|---|---|---|---|
| nbr.val | 1459.00 | 1459.00 | 1459.00 | 1459.00 | 1459.00 | 1459.00 |
| nbr.null | 1.00 | 729.00 | 0.00 | 0.00 | 0.00 | 64.00 |
| nbr.na | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| min | −729.00 | 0.00 | 101.83 | 0.84 | 0.28 | 0.00 |
| max | 729.00 | 1.00 | 191.12 | 7.43 | 6.62 | 2.88 |
| range | 1458.00 | 1.00 | 89.30 | 6.59 | 6.34 | 2.88 |
| sum | 0.00 | 730.00 | 179337.11 | 5023.48 | 4610.78 | 1356.98 |
| median | 0.00 | 1.00 | 122.42 | 3.40 | 3.12 | 0.85 |
| mean | 0.00 | 0.50 | 122.92 | 3.44 | 3.16 | 0.93 |
| SE.mean | 11.03 | 0.01 | 0.20 | 0.03 | 0.03 | 0.01 |
| CI.mean.0.95 | 21.64 | 0.03 | 0.39 | 0.05 | 0.05 | 0.03 |
| var | 177511.67 | 0.25 | 57.49 | 0.98 | 1.07 | 0.28 |
| std.dev | 421.32 | 0.50 | 7.58 | 0.99 | 1.04 | 0.53 |
| coef.var | Inf | 1.00 | 0.06 | 0.29 | 0.33 | 0.57 |

Figure 1: Descriptive statistics of the data

# Method

Because the purpose of this paper is to validate the impact of the Minimum Legal Drinking Age (MLDA) over the most alcohol influenced crimes, we conducted Regression Discontinuity Design (RDD). The RDD estimates impact around the eligibility cutoff, in our case MLDA, as the difference between the average outcome for units on the treated side (MLDA and over) of the eligibility cutoff and the average outcome of units on the untreated (under MLDA) side of the cutoff (MLDA).

According to the researchers of our reference study, after applying their research through several surveys to inmates and other techniques, they found the fifteen most affected crimes by Alcohol consumption. For this investigation, we focused on the crimes classified as High-alcohol usage from the reference paper. These are Assault, Rape, Arson, and Murder, based on the role alcohol plays when an offender commits a given crime.

# Ethical Issues

# Weaknesses and Limitations

https://journals-scholarsportal-info.myaccess.library.utoronto.ca/details/01953613/v36i0002/103_acdacinyc.xml

Alcohol intake we don't know

As these authors acknowledge in their literature review, a drawback of the age-related research is that it relies on arrest data in order to ascertain age, and it is possible that the effect of alcohol on arrests is not due to crime commission, but to an increased chance of getting caught.

The primary one is that although our approach recovers a causal estimate of the reduced-form effect of the MLDA on arrests, we cannot provide direct evidence on the underlying mechanisms or clean estimates of the persistence of the effects. Though previous research used RDD methods and various survey data sets to show that alcohol consumption increases sharply at the MLDA (Carpenter & Dobkin, 2009; SAMHSA/OAS, 2009; Crost & Guerrero, 2012) and this is likely the primary cause of the increase, other factors might also contribute to the increase in arrest rates we document in this paper.11

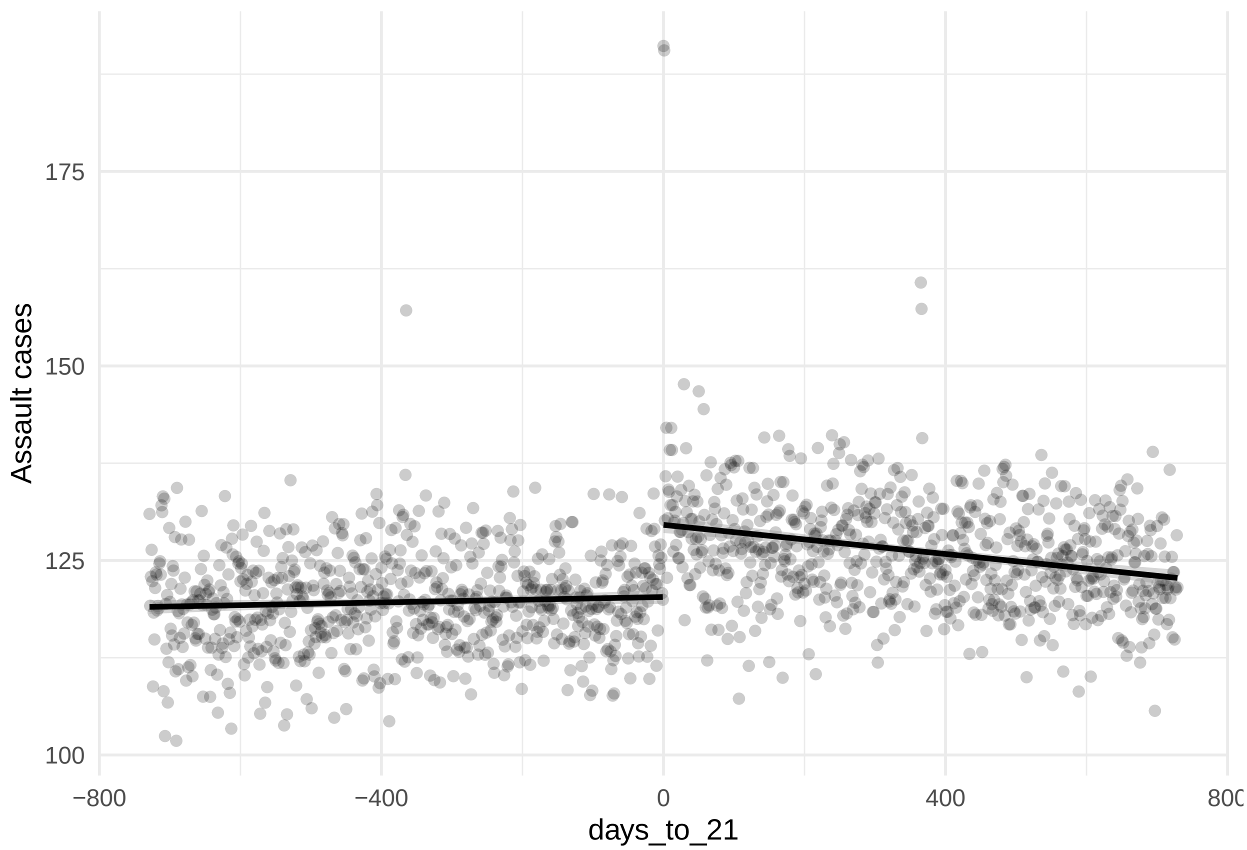
A second possibility is that people over the drinking age may be more likely to drink in public places such as bars, where crimes may be more likely to result in an arrest (i.e., we may observe changes in arrest behavior that simply reflect changes in venue).

Because violent crimes – particularly murder, manslaughter, and rape – are relatively uncommon, we are limited somewhat by statistical precision when we disaggregate by specific violent crime type.30

Lack of instrumental variable

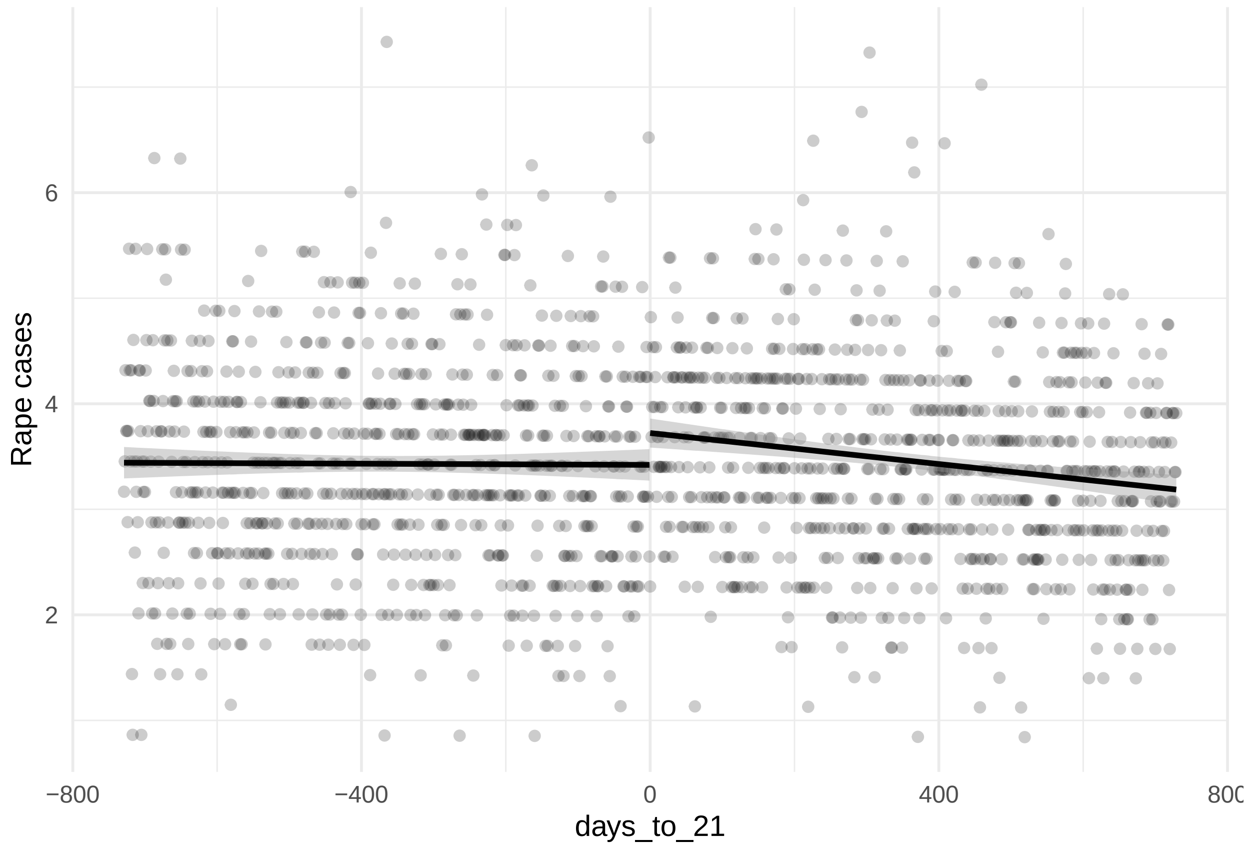
## Analysis

### Assault



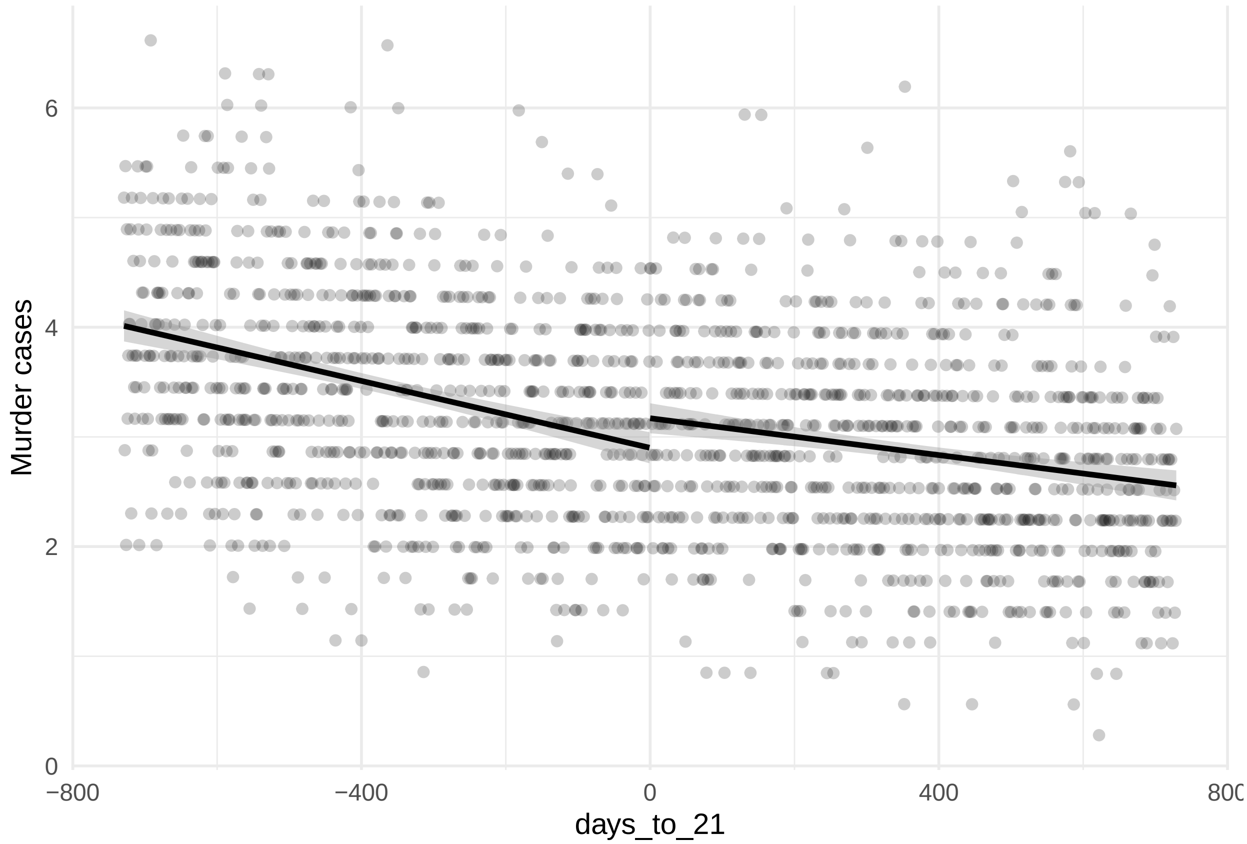

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 118 | 0.399 | 297 | 0 |
| days_to_21 | -0.00381 | 0.000846 | -4.51 | 7.13e-06 |
| mlda_and_over | 9.28 | 0.713 | 13 | 9.9e-37 |

## Rape



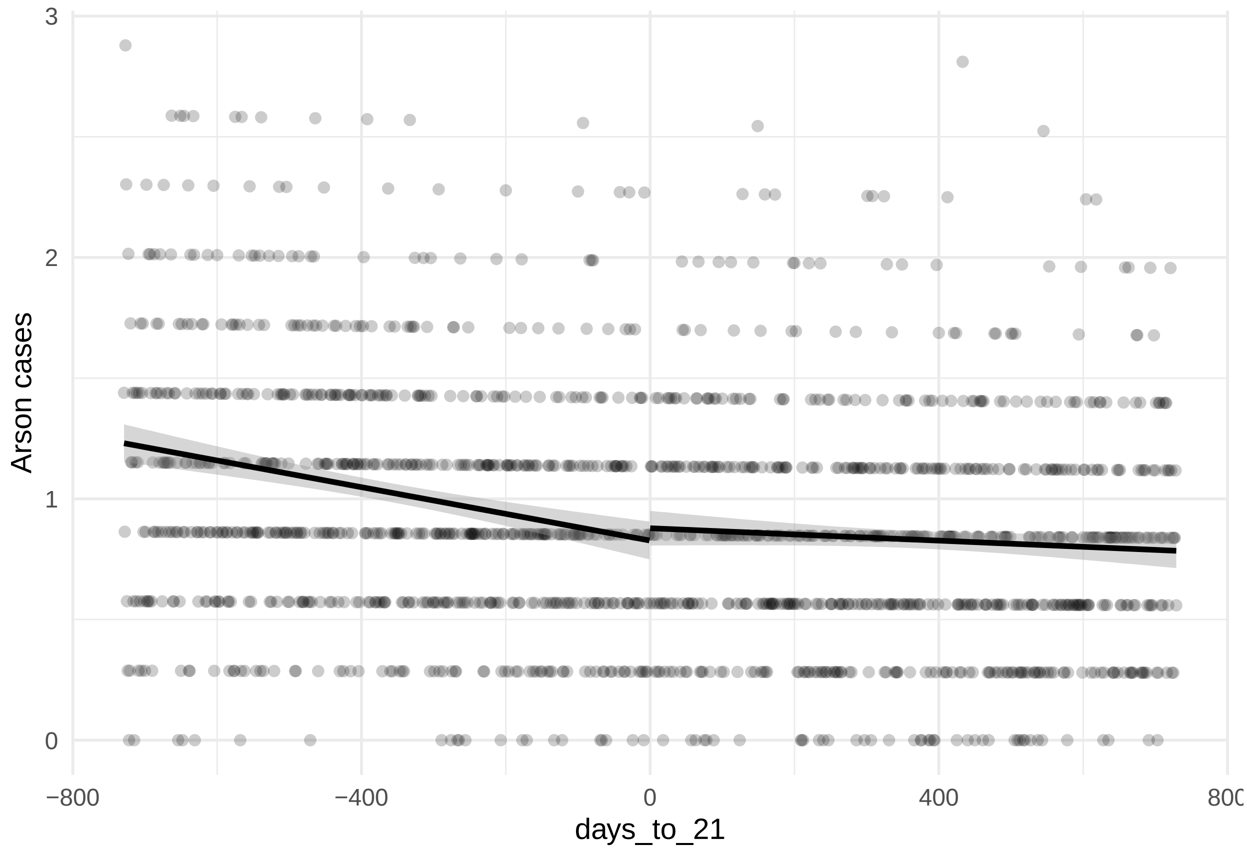

| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 3.29 | 0.0579 | 56.8 | 0 |
| days_to_21 | -0.000382 | 0.000123 | -3.11 | 0.00194 |
| mlda_and_over | 0.302 | 0.104 | 2.92 | 0.00358 |

## Murder




| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 3.03 | 0.0564 | 53.7 | 0 |
| days_to_21 | -0.00118 | 0.00012 | -9.88 | 2.56e-22 |
| mlda_and_over | 0.269 | 0.101 | 2.67 | 0.00763 |

## Arson




| term | estimate | std.error | statistic | p.value |
|---|---|---|---|---|
| (Intercept) | 0.905 | 0.0304 | 29.8 | 8.29e-153 |
| days_to_21 | -0.00034 | 6.44e-05 | -5.28 | 1.49e-07 |
| mlda_and_over | 0.0506 | 0.0543 | 0.933 | 0.351 |

# Appendix A

```r
knitr::opts_chunk$set(echo = FALSE, include = FALSE)
# import libraries
library(broom)
library(tidyverse)
library(gridExtra)
library(pastecs)
library(readxl)
library(dplyr)
library(tidyr)
library(ggplot2)
library(reshape2)
library(stringr)
library(knitr)
library(huxtable)
library(jtools)

setwd("~/Experimental Design for Data Science/ProblemSet5")
drinking <- read.csv("P01 Age Profile of Arrest Rates 1979-2006.csv")
drinking <- janitor::clean_names(drinking)

head(drinking)
top4_crimes_19_to_23 <- filter(drinking, days_to_21 > -730 &
    days_to_21 < 730)
top4_crimes_19_to_23 <- select(top4_crimes_19_to_23, days_to_21,
    assault_r, rape_r, murder_r, arson_r)

top4_crimes_19_to_23 <- top4_crimes_19_to_23 %>% mutate(mlda_and_over = if_else(days_to_21 <
    0, 0, 1))


# Compute descriptive statistics - boxplots
p1 <- ggplot(top4_crimes_19_to_23) + aes(y = assault_r) + geom_boxplot() +
    labs(x = "", y = "Assault rate")
p2 <- ggplot(top4_crimes_19_to_23) + aes(y = rape_r) + geom_boxplot() +
    labs(x = "", y = "Rape rate")
p3 <- ggplot(top4_crimes_19_to_23) + aes(y = murder_r) + geom_boxplot() +
    labs(x = "", y = "Murder rate")
p4 <- ggplot(top4_crimes_19_to_23) + aes(y = arson_r) + geom_boxplot() +
    labs(x = "", y = "Arson rate")
grid1 <- grid.arrange(p1, p2, p3, p4, ncol = 2, nrow = 2)
# Select only top4
only_top4 <- top4_crimes_19_to_23
# Compute descriptive statistics - table
tt1 <- ttheme_default()

stats_table <- stat.desc(top4_crimes_19_to_23)
stats_table <- round(stats_table, 2)
stats_table <- mutate(stats_table, stats = row.names(stats_table))
stats_table <- select(stats_table, stats, days_to_21, mlda_and_over,
    assault_r, rape_r, murder_r, arson_r)
colnames(stats_table) <- c("stats", "days_to_21 ", "mlda_and_over",
```

```r
    "assault", "rape", "murder", "arson")
grid2 <- grid.arrange(tableGrob(stats_table, theme = tt1, rows = NULL),
    ncol = 1, nrow = 1)

# Join the boxplots and the table
grid.arrange(arrangeGrob(grid1, ncol = 1, nrow = 1), arrangeGrob(grid2,
    ncol = 1, nrow = 1), heights = c(15, 1), widths = c(1, 2),
    bottom = "Figure 1: Descriptive statistics of the data")

# Plot assault cases
top4_crimes_19_to_23 %>% ggplot(aes(x = days_to_21, y = assault_r)) +
    geom_point(alpha = 0.2) + geom_smooth(data = top4_crimes_19_to_23 %>%
    filter(days_to_21 < 0), method = "lm", color = "black") +
    geom_smooth(data = top4_crimes_19_to_23 %>% filter(days_to_21 >=
        0), method = "lm", color = "black") + theme_minimal() +
    labs(x = "days_to_21", y = "Assault cases")


lm(assault_r ~ days_to_21 + mlda_and_over, data = top4_crimes_19_to_23) %>%
    tidy()


# Plot assault cases
top4_crimes_19_to_23 %>% ggplot(aes(x = days_to_21, y = rape_r)) +
    geom_point(alpha = 0.2) + geom_smooth(data = top4_crimes_19_to_23 %>%
    filter(days_to_21 < 0), method = "lm", color = "black") +
    geom_smooth(data = top4_crimes_19_to_23 %>% filter(days_to_21 >=
        0), method = "lm", color = "black") + theme_minimal() +
    labs(x = "days_to_21", y = "Rape cases")


lm(rape_r ~ days_to_21 + mlda_and_over, data = top4_crimes_19_to_23) %>%
    tidy()

# Plot assault cases
top4_crimes_19_to_23 %>% ggplot(aes(x = days_to_21, y = murder_r)) +
    geom_point(alpha = 0.2) + geom_smooth(data = top4_crimes_19_to_23 %>%
    filter(days_to_21 < 0), method = "lm", color = "black") +
    geom_smooth(data = top4_crimes_19_to_23 %>% filter(days_to_21 >=
        0), method = "lm", color = "black") + theme_minimal() +
    labs(x = "days_to_21", y = "Murder cases")


lm(murder_r ~ days_to_21 + mlda_and_over, data = top4_crimes_19_to_23) %>%
    tidy()

# Plot assault cases
top4_crimes_19_to_23 %>% ggplot(aes(x = days_to_21, y = arson_r)) +
    geom_point(alpha = 0.2) + geom_smooth(data = top4_crimes_19_to_23 %>%
    filter(days_to_21 < 0), method = "lm", color = "black") +
    geom_smooth(data = top4_crimes_19_to_23 %>% filter(days_to_21 >=
        0), method = "lm", color = "black") + theme_minimal() +
    labs(x = "days_to_21", y = "Arson cases")
```

```
lm(arson_r ~ days_to_21 + mlda_and_over, data = top4_crimes_19_to_23) %>%
    tidy()
```

## References