# Car Jacking MPLS - Tract

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## Spatial Data

```
#MN tracts
tracts <- get_acs(geography = "tract",
                  state = "MN",
                variables = "B01001_001E",
                output = "wide",
                survey = "acs5",
                year = 2020,
                geometry = T)
```

```
##   |                                                                              |
```

```
#Minneapolis Shapefile
mpls <- st_read("Data/mpls_city-shp/16cdbbfa-ad10-493c-afaf-52b61f2e76e42020329-1-180h9ap.whbo.shp") %>%
   st_transform(st_crs(tracts))
```

```
## Reading layer `16cdbbfa-ad10-493c-afaf-52b61f2e76e42020329-1-180h9ap.whbo' from data source `C:\User
##   using driver `ESRI Shapefile'
## Simple feature collection with 1 feature and 4 fields
## Geometry type: POLYGON
## Dimension:     XY
## Bounding box:  xmin: -93.32911 ymin: 44.89059 xmax: -93.19433 ymax: 45.05125
## Geodetic CRS:  WGS 84
```

```
mpls_tract <- tracts %>%
  st_filter(mpls, .predicate = st_intersects) %>%
  mutate(GEOID = as.numeric(GEOID),
         tract_area = as.numeric(st_area(.)),
         tract_area_sqkm = tract_area*.000001,
         tract_area_sqmi = tract_area_sqkm*.386102,
         intersection_area = as.numeric(st_area(st_intersection(., mpls))),
         perc_intersection = intersection_area/tract_area*100) %>%
  filter(perc_intersection >= 2) %>%
  select(-"B01001_001M")
```

## ACS Covariates

```
acs_17 <- get_acs(
  geography = "tract",
  variables = c("B01001_001E"),
  year = 2017,
```

```
  state = "MN",
  county = "Hennepin",
  geometry = TRUE) %>%
  select(estimate)
```

```
## Getting data from the 2013-2017 5-year ACS

## Downloading feature geometry from the Census website.  To cache shapefiles for use in future session

##   |                                                                              |
```

```
acs_18 <- get_acs(
  geography = "tract",
  variables = c("B01001_001E"),
  year = 2018,
  state = "MN",
  county = "Hennepin",
  geometry = TRUE
) %>%
select(estimate)
```

```
## Getting data from the 2014-2018 5-year ACS
## Downloading feature geometry from the Census website.  To cache shapefiles for use in future session

##   |                                                                              |
```

```
acs_19 <- get_acs(
  geography = "tract",
  variables = c("B01001_001E"),
  year = 2019,
  state = "MN",
  county = "Hennepin",
  geometry = TRUE
) %>%
select(estimate)
```

```
## Getting data from the 2015-2019 5-year ACS
## Downloading feature geometry from the Census website.  To cache shapefiles for use in future session

##   |                                                                              |
```

```
acs_20 <- get_acs(
  geography = "tract",
  variables = c("B01001_001E"),
  year = 2020,
  state = "MN",
  county = "Hennepin",
  geometry = TRUE
 )
```

```
## Getting data from the 2016-2020 5-year ACS
## Downloading feature geometry from the Census website.  To cache shapefiles for use in future session
```

```
library(tigris)
```

```
## To enable caching of data, set `options(tigris_use_cache = TRUE)`
## in your R script or .Rprofile.
```

```r
hennepin_blocks <- blocks(
  "MN",
  "Hennepin",
  year = 2020
)
```

```
##   |                                                                              |
```

```r
#2017 ACS interpolation
acs_1720 <- interpolate_pw(
  from = acs_17,
  to = acs_20,
  to_id = "GEOID",
  weights = hennepin_blocks,
  weight_column = "POP20",
  crs = 26993,
  extensive = TRUE) %>%
  mutate(year = 2017)

#2018 ACS interpolation
acs_1820 <- interpolate_pw(
  from = acs_18,
  to = acs_20,
  to_id = "GEOID",
  weights = hennepin_blocks,
  weight_column = "POP20",
  crs = 26993,
  extensive = TRUE) %>%
  mutate(year = 2018)


#2019 ACS interpolation
acs_1920 <- interpolate_pw(
  from = acs_19,
  to = acs_20,
  to_id = "GEOID",
  weights = hennepin_blocks,
  weight_column = "POP20",
  crs = 26993,
  extensive = TRUE) %>%
  mutate(year = 2019)


pop_denoms <- acs_20 %>%
  st_transform(crs = 26993) %>%
  mutate(year = 2020) %>%
  select(-moe, -variable, -NAME) %>%
  rbind(acs_1720, acs_1820, acs_1920) %>%
  filter(GEOID %in% mpls_tract$GEOID)

#2021+2022: LOCF
pop_denom_21 <- pop_denoms %>%
  filter(year==2020) %>%
  select(GEOID, year, estimate) %>%
```

```r
  mutate(year = 2021)

pop_denom_22 <- pop_denoms %>%
  filter(year==2020) %>%
  select(GEOID, year, estimate) %>%
  mutate(year = 2022)

pop_denom_locf <- pop_denoms %>%
  rbind(pop_denom_21, pop_denom_22) %>%
  rename(total_pop = estimate) %>%
  mutate(GEOID = as.numeric(GEOID)) %>%
  st_drop_geometry()

#ACS 2020 L-2 covariates
acs_2020 <- get_acs(geography = "tract",
            state = "MN",
               variables = c("B01001_001E", "B03002_003E", "B03002_004E", "B03002_005E",
                             "B03002_006E", "B03002_007E", "B03002_008E", "B03002_009E",
                             "B03002_010E", "B03002_011E", "B03002_012E", "B23025_002E",
                             "B23025_005E", "B17001_002E", "B19057_002E", "B11003_015E",
                             "B06009_002E", "B06009_005E", "C24010_001E", "C24010_003E",
                             "C24010_039E", "B11001_003E", "B01001_002E", "B05001_006E",
                             "B01001_003E", "B01001_004E", "B01001_005E", "B01001_006E",
                             "B01001_007E", "B01001_008E", "B01001_009E", "B01001_010E",
                             "B01001_011E", "B01001_012E", "B01001_013E", "B01001_014E",
                             "B01001_015E", "B01001_016E", "B01001_017E", "B01001_018E",
                             "B01001_019E", "B01001_020E", "B01001_021E", "B01001_022E",
                             "B01001_023E", "B01001_024E", "B01001_025E", "B01001_027E",
                             "B01001_028E", "B01001_029E", "B01001_030E", "B01001_031E",
                             "B01001_032E", "B01001_033E", "B01001_034E", "B01001_035E",
                             "B01001_036E", "B01001_037E", "B01001_038E", "B01001_039E",
                             "B01001_040E", "B01001_041E", "B01001_042E", "B01001_043E",
                             "B01001_044E", "B01001_045E", "B01001_046E", "B01001_047E",
                             "B01001_048E", "B01001_049E", "B07001_017E", "B25003_002E",
                             "B05002_013E", "B19013_001E"),
               output = "wide",
               survey = "acs5",
               year = 2020) %>%
  select(-ends_with("M", ignore.case = F)) %>%
  rename(total_pop = B01001_001E, white_pop = B03002_003E, black_pop = B03002_004E,
         na_pop = B03002_005E, asian_pop = B03002_006E, hpi_pop = B03002_007E,
         other_pop = B03002_008E, biracial_pop = B03002_009E, biracial_other_pop = B03002_010E,
         biracial_three_pop = B03002_011E, hisp_pop = B03002_012E, total_ilf = B23025_002E,
         unemp = B23025_005E, povlevel = B17001_002E, pub_assist = B19057_002E,
         female_hh = B11003_015E, no_hs_dip = B06009_002E, bach_degree = B06009_005E,
         total_employed = C24010_001E, employed_mbsa_male = C24010_003E,
         employed_mbsa_female = C24010_039E, mar_fam = B11001_003E, male = B01001_002E,
         noncitizen = B05001_006E,
        age_m_5_under = B01001_003E, age_m_5_9 = B01001_004E, age_m_10_14 = B01001_005E,
        age_m_15_17 = B01001_006E, age_m_18_19 = B01001_007E, age_m_20 = B01001_008E,
        age_m_21 = B01001_009E, age_m_22_24 = B01001_010E, age_m_25_29 = B01001_011E,
        age_m_30_34 = B01001_012E, age_m_35_39 = B01001_013E, age_m_40_44 = B01001_014E,
        age_m_45_49 = B01001_015E, age_m_50_54 = B01001_016E, age_m_55_59 = B01001_017E,
```

```
       age_m_60_61 = B01001_018E, age_m_62_64 = B01001_019E, age_m_65_66 = B01001_020E,
       age_m_67_69 = B01001_021E, age_m_70_74 = B01001_022E, age_m_75_79 = B01001_023E,
       age_m_80_84 = B01001_024E, age_m_85_plus = B01001_025E, age_f_5_under = B01001_027E,
       age_f_5_9 = B01001_028E, age_f_10_14 = B01001_029E, age_f_15_17 = B01001_030E,
       age_f_18_19 = B01001_031E, age_f_20 = B01001_032E, age_f_21 = B01001_033E,
       age_f_22_24 = B01001_034E, age_f_25_29 = B01001_035E, age_f_30_34 = B01001_036E,
       age_f_35_39 = B01001_037E, age_f_40_44 = B01001_038E, age_f_45_49 = B01001_039E,
       age_f_50_54 = B01001_040E, age_f_55_59 = B01001_041E, age_f_60_61 = B01001_042E,
       age_f_62_64 = B01001_043E, age_f_65_66 = B01001_044E, age_f_67_69 = B01001_045E,
       age_f_70_74 = B01001_046E, age_f_75_79 = B01001_047E, age_f_80_84 = B01001_048E,
       age_f_85_plus = B01001_049E, res_mob = B07001_017E,
       own_hh = B25003_002E, foreign = B05002_013E,
       med_hh_inc = B19013_001E) %>%
  mutate(white_prop = white_pop/total_pop,
         black_prop = black_pop/total_pop,
         na_prop = na_pop/total_pop,
         asian_prop = asian_pop/total_pop,
         hpi_prop = hpi_pop/total_pop,
         other_prop = other_pop/total_pop,
         biracial_prop = (biracial_pop+biracial_other_pop+biracial_three_pop)/total_pop,
         hisp_prop = hisp_pop/total_pop,
         white_perc = 100*white_pop/total_pop,
         black_perc = 100*black_pop/total_pop,
         na_perc = 100*na_pop/total_pop,
         asian_perc = 100*asian_pop/total_pop,
         hpi_perc = 100*hpi_pop/total_pop,
         other_perc = 100*other_pop/total_pop,
         biracial_perc = 100*(biracial_pop+biracial_other_pop+biracial_three_pop)/total_pop,
         hisp_perc = 100*hisp_pop/total_pop,
         unemp_rate = 100*unemp/total_ilf,
         pov_rate = 100*povlevel/total_pop,
         pub_assist_rate = 100*pub_assist/total_pop,
         female_hh_rate = 100*female_hh/total_pop,
         no_hs_dip_rate = 100*no_hs_dip/total_pop,
         bach_degree_rate = 100*bach_degree/total_pop,
         employed_mbsa = employed_mbsa_male+employed_mbsa_female,
         employed_mbsa_rate = 100*employed_mbsa/total_employed,
         mar_fam_rate = 100*mar_fam/total_pop,
         male_rate = 100*male/total_pop,
         noncitizen_rate = 100*noncitizen/total_pop,
         race_eth_hetero  = 1-(white_prop^2+black_prop^2+na_prop^2+asian_prop^2+
                      hpi_prop^2+other_prop^2+other_prop^2+biracial_prop^2+hisp_prop^2),
         age_below_18_perc = 100*(age_m_5_under+age_f_5_under+age_m_5_9+
                            age_f_5_9+age_m_10_14+age_f_10_14+age_m_15_17+
                            age_f_15_17)/total_pop,
         age_19_29_perc = 100*(age_m_18_19+age_f_18_19+age_m_20+age_f_20+age_m_21+age_f_21+
                         age_m_22_24+age_f_22_24+age_m_25_29+age_f_25_29)/total_pop,
         age_30_49_perc = 100*(age_m_30_34+age_f_30_34+age_m_35_39+age_f_35_39+
                          age_m_40_44+age_f_40_44+age_m_45_49+age_f_45_49)/total_pop,
         age_50_69_perc = 100*(age_m_50_54+age_f_50_54+age_m_55_59+age_f_55_59+
                          age_m_60_61+age_f_60_61+age_m_62_64+age_f_62_64+
                          age_m_65_66+age_f_65_66+age_m_67_69+age_f_67_69)/total_pop,
         age_70_plus_perc = 100*(age_m_70_74+age_f_70_74+age_m_75_79+age_f_75_79+
```

```
                                  age_m_80_84+age_f_80_84+age_m_85_plus+age_f_85_plus)/total_pop,
         res_mob_rate = 100-100*res_mob/total_pop,
         own_hh_rate = 100*own_hh/total_pop,
         foreign_rate = 100*foreign/total_pop)
```

```
## Getting data from the 2016-2020 5-year ACS
```

# Open Minneapolis Carjacking Data

```
#open minneapolis crime data 2019-4/7 (date of download)
cj_spatial <- read_csv("Car Jacking/crime_data.csv")  %>%
  filter(Offense=="Carjacking - Subset of Robbery") %>% #filter carjackings
  mutate(date=ymd_hms(Occurred_Date),
         year=isoyear(date),
         week=isoweek(date)) %>%
  select(OBJECTID, year, week, Latitude, Longitude) %>%
  st_as_sf(coords = c("Longitude", "Latitude"), crs = "NAD83", remove=F) %>%
  st_join(mpls_tract) %>% #spatial join neighborhoods
  st_drop_geometry() %>%
  filter(!is.na(GEOID)) %>%
  group_by(year, week, GEOID, .drop=F) %>%
  tally(name = "car_jack") %>%
  ungroup() %>%
  complete(year, week, GEOID=mpls_tract$GEOID, fill = list(car_jack = 0)) %>%
  filter(!(year==2022 & week >= 14) & #removing unobserved/redundant completions
           !(year==2021 & week==53) & #removing unobserved/redundant completions
           !(year==2020 & week < 36)) %>% #removing weeks before Sept. 2020, isoweek 36
  arrange(GEOID, year, week) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  left_join(pop_denom_locf, by = c("GEOID", "year")) %>%
  mutate(car_jack_rate = car_jack/total_pop*1000) %>%
  st_as_sf()
```

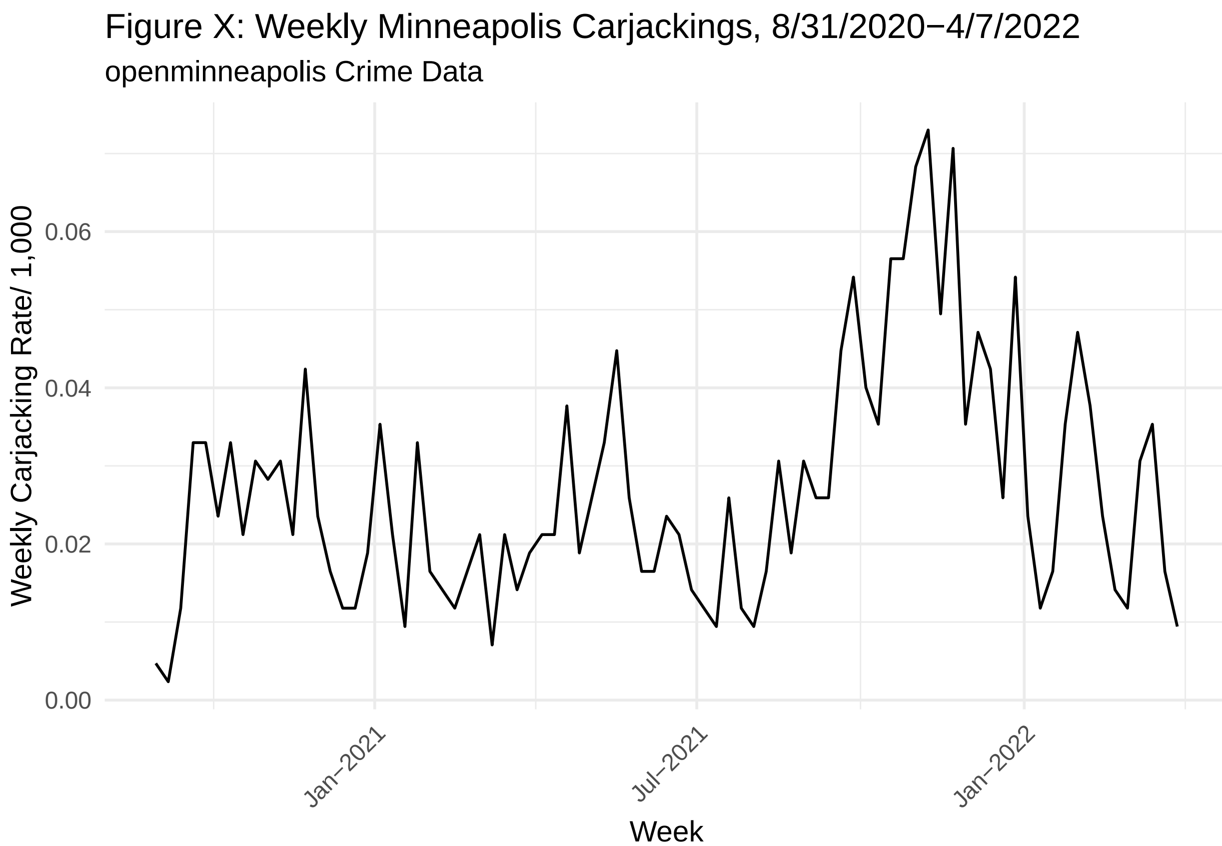
# MPLS Carjackings by Week

```
#aggregate to week over tracts
cj_week <- cj_spatial %>%
  group_by(year, week) %>%
  summarize(car_jack = sum(car_jack, na.rm = T),
            total_pop = sum(total_pop, na.rm = T)) %>%
  mutate(begin_date = ISOweek2date(paste(year, paste0("W", sprintf("%02d", week)), 1,sep = "-")),
         end_date = begin_date+weeks(1)-days(1),
         car_jack_rate = car_jack/total_pop*1000)
```

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

```
ggplot(cj_week)+
  geom_line(aes(x=begin_date, y=car_jack_rate))+
  scale_x_date(date_labels = "%b-%Y",
               limits = c(min(cj_week$begin_date), max(cj_week$begin_date)))+
  labs(title = "Figure X: Weekly Minneapolis Carjackings, 8/31/2020-4/7/2022",
```

```r
      subtitle = "openminneapolis Crime Data",
      x = "Week",
      y = "Weekly Carjacking Rate/ 1,000")+
  theme_minimal()+
    theme(axis.text.x=element_text(angle=45, hjust=1))
```




## MPLS ZCTA Carjackings Map

```r
#aggregate to neighborhood-year level
cj_tract_year <- cj_spatial %>%
  group_by(GEOID, year) %>%
  summarize(car_jack = sum(car_jack, na.rm = T),
            total_pop = sum(B01001_001E, na.rm = T),
            car_jack_rate = car_jack/total_pop*1000)
```

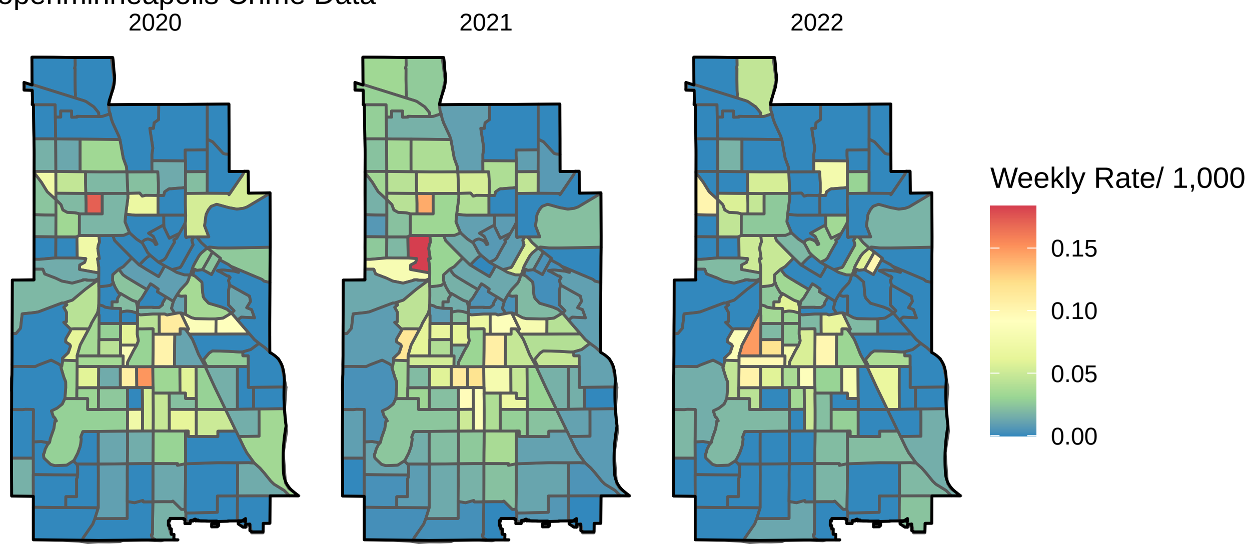
```
## `summarise()` has grouped output by 'GEOID'. You can override using the
## `.groups` argument.
```

```r
ggplot() +
  geom_sf(data = cj_tract_year, aes(geometry = geometry, fill = car_jack_rate)) +
  geom_sf(data = mpls, aes(geometry = geometry), color = "black", alpha = 0)+
  facet_wrap(~year)+
  scale_fill_distiller(palette = "Spectral")+
  labs(title = "Figure X: Minneapolis Carjacking Rates by Tract and Year",
      subtitle = "openminneapolis Crime Data",
```

```
      fill = "Weekly Rate/ 1,000")+
  theme_void()
```

Figure X: Minneapolis Carjacking Rates by Tract and Year

openminneapolis Crime Data




## Expanded MPLS Carjacking (Crime Incidents) Data

```
cj_exp <- read_csv("Data/MPDdata_082422.csv") %>%
   mutate(date=mdy_hm(reporteddate),
         year=isoyear(date),
         week=isoweek(date)) %>%
  select(CaseNumber, year, week, latitude, longitude) %>%
  distinct(CaseNumber, .keep_all = TRUE) %>%
  drop_na(latitude, longitude) %>%
  st_as_sf(coords = c("longitude", "latitude"), crs = "NAD83", remove=F) %>%
  st_join(mpls_tract) %>% #spatial join neighborhoods
  st_drop_geometry() %>%
  drop_na(GEOID) %>%
  group_by(year, week, GEOID, .drop=F) %>%
  tally(name = "car_jack") %>%
  ungroup() %>%
  complete(year, week, GEOID=mpls_tract$GEOID, fill = list(car_jack = 0)) %>%
  filter(!(year==2021 & week==53)) %>%
  arrange(GEOID, year, week) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  left_join(pop_denom_locf, by = c("GEOID", "year")) %>%
```

```
  mutate(car_jack_rate = car_jack/total_pop*1000) %>%
  st_as_sf()
```

```
## Rows: 3894 Columns: 28
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (24): CaseNumber, dataset, closurecode, closurecode_MPD, reporteddate, c...
## dbl  (4): precinct, latitude, longitude, age
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

## MPLS Carjackings by Week - MPD Extended Data

```
#aggregate to week over tracts
cj_exp_week <- cj_exp %>%
  group_by(year, week) %>%
  summarize(car_jack = sum(car_jack, na.rm = T),
            total_pop = sum(total_pop, na.rm = T)) %>%
  mutate(begin_date = ISOweek2date(paste(year, paste0("W", sprintf("%02d", week)), 1,sep = "-")),
         end_date = begin_date+weeks(1)-days(1),
         car_jack_rate = car_jack/total_pop*1000,
         pre_post_floyd = ifelse(end_date <= as.Date("2020-05-25"), 0, 1)) %>%
  filter(end_date <= as.Date("2022-08-20"))
```

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

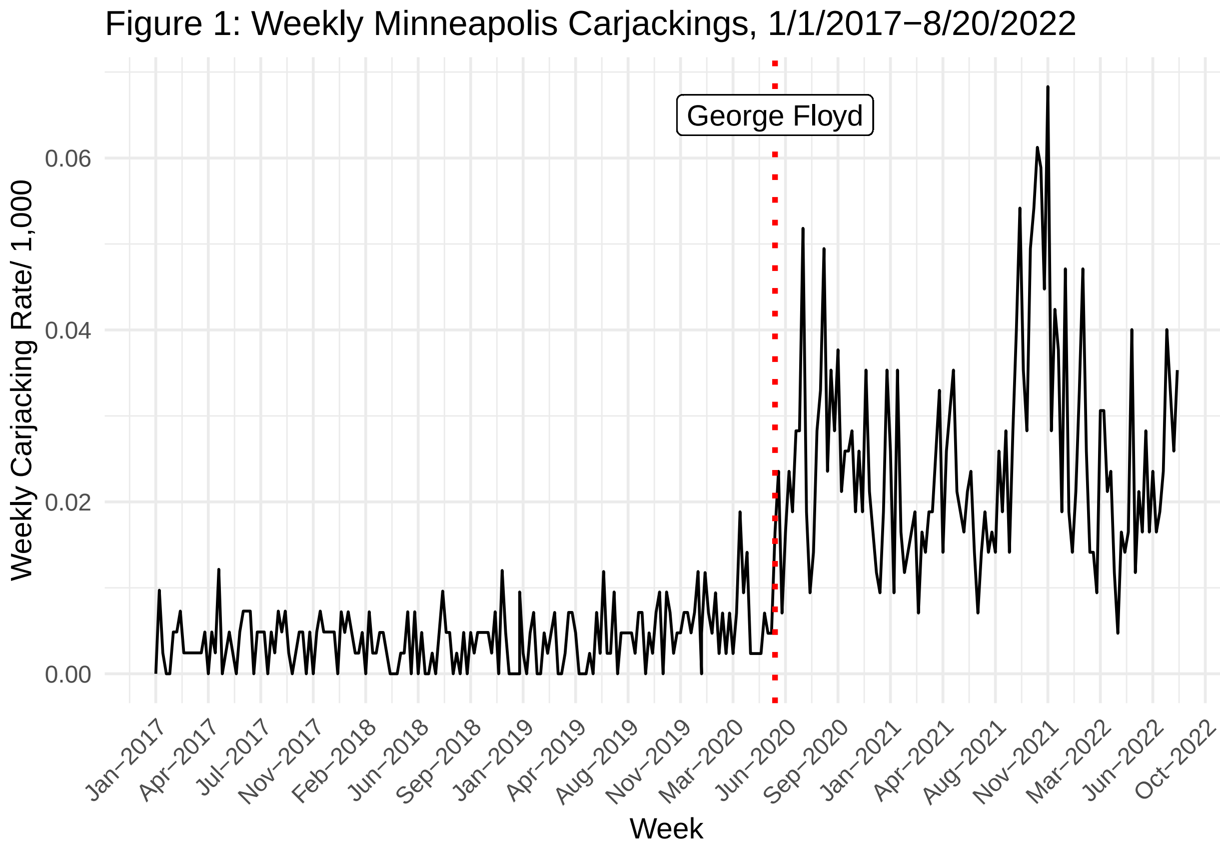
```
pre_mean <- mean(cj_exp_week$car_jack_rate[cj_exp_week$pre_post_floyd==0], na.rm = T)
post_mean <- mean(cj_exp_week$car_jack_rate[cj_exp_week$pre_post_floyd==1], na.rm = T)

c(pre_mean, post_mean)
```

```
## [1] 0.004044021 0.024976559
```

```
post_mean/pre_mean
```

```
## [1] 6.176169
```

```
ggplot(cj_exp_week)+
  geom_line(aes(x=begin_date, y=car_jack_rate))+
  scale_x_date(date_labels = "%b-%Y", date_breaks = "15 weeks",
               limits = c(min(cj_exp_week$begin_date), max(cj_exp_week$begin_date)))+
  geom_vline(xintercept=cj_exp_week$begin_date[cj_exp_week$year==2020 &
                                                cj_exp_week$week==isoweek(date("2020-05-25"))],
             linetype="dotted", color="red", size=1)+
   geom_label(aes(x=cj_exp_week$begin_date[cj_exp_week$year==2020 &
                                            cj_exp_week$week==isoweek(date("2020-05-25"))],
                 y=0.065),
             label = "George Floyd", show.legend = FALSE)+
  labs(title = "Figure 1: Weekly Minneapolis Carjackings, 1/1/2017-8/20/2022",
       x = "Week",
       y = "Weekly Carjacking Rate/ 1,000")+
  theme_minimal()+
    theme(axis.text.x=element_text(angle=45, hjust=1))
```




```
ggsave(filename = "Car Jacking/Figures for PAA/fig1.png", bg="white", width = 10, height = 8)
```

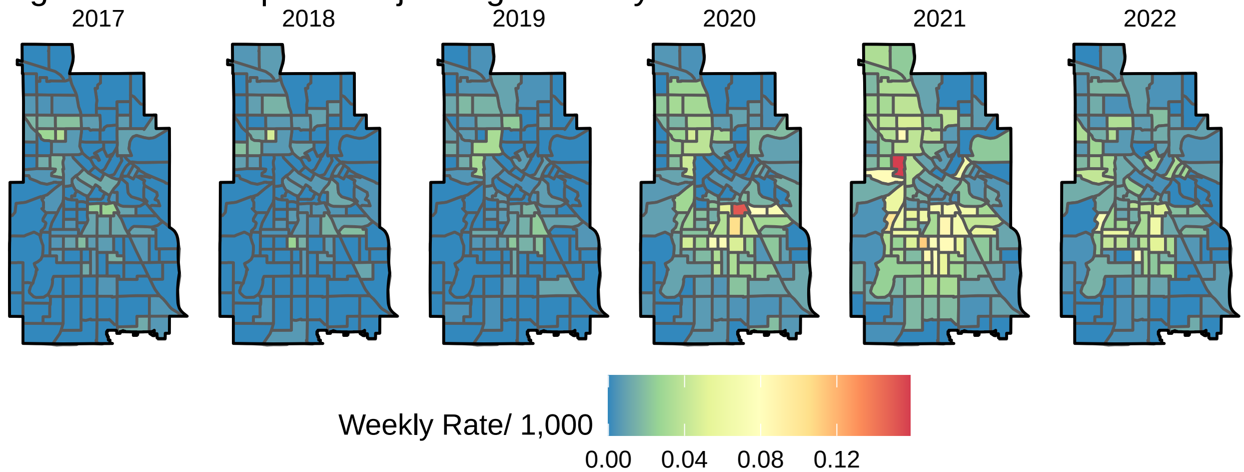
## MPLS ZCTA Carjackings Map - MPD Extended Data

```
#aggregate to neighborhood-year level
cj_exp_tract_year <- cj_exp %>%
  group_by(GEOID, year) %>%
  summarize(car_jack = sum(car_jack, na.rm = T),
            total_pop = sum(B01001_001E, na.rm = T),
            car_jack_rate = car_jack/total_pop*1000) %>%
  mutate(GEOID = as.character(GEOID))
```

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

```
ggplot() +
  geom_sf(data = cj_exp_tract_year, aes(geometry = geometry, fill = car_jack_rate)) +
  geom_sf(data = mpls, aes(geometry = geometry), color = "black", alpha = 0)+
  facet_grid(~year)+
  scale_fill_distiller(palette = "Spectral")+
  labs(title = "Figure 2: Minneapolis Carjacking Rates by Tract and Year",
       fill = "Weekly Rate/ 1,000")+
  theme_void()+
  theme(legend.key.size = unit(0.8, "cm"),legend.position = "bottom")
```

Figure 2: Minneapolis Carjacking Rates by Tract and Year




```r
ggsave(filename = "Car Jacking/Figures for PAA/fig2.png", bg="white", width = 10, height = 8)
```

## MPLS Murder (Crime Incidents) Data

```r
#pre-pims
mpd_2016 <- read_csv("Data/Police_Incidents_2016.csv")
```

```
## Rows: 20155 Columns: 20
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (12): PublicAddress, CCN, Precinct, ReportedDate, BeginDate, Offense, D...
## dbl   (7): FID, ControlNbr, GBSID, Lat, Long, X, Y
## time  (1): Time
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
mpd_2017 <- read_csv("Data/Police_Incidents_2017.csv")
```

```
## Rows: 22085 Columns: 20
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (12): PublicAddress, CCN, Precinct, ReportedDate, BeginDate, Offense, D...
## dbl   (7): FID, ControlNbr, GBSID, Lat, Long, X, Y
## time  (1): Time
##
```

```
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
mpd_2018a <- read_csv("Data/Police_Incidents_2018.csv")
```

```
## Rows: 7350 Columns: 20
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (12): PublicAddress, CCN, Precinct, ReportedDate, BeginDate, Offense, D...
## dbl   (7): FID, ControlNbr, GBSID, Lat, Long, X, Y
## time  (1): Time
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
#pims
mpd_2018b <- read_csv("Data/Police_Incidents_2018_PIMS.csv")
```

```
## Rows: 11603 Columns: 23
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (13): publicaddress, caseNumber, precinct, reportedDate, beginDate, repo...
## dbl (10): X, Y, reportedTime, beginTime, centergbsid, centerLong, centerLat,...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
mpd_2019 <- read_csv("Data/Police_Incidents_2019.csv")
```

```
## Warning: One or more parsing issues, see `problems()` for details
```

```
## Rows: 22934 Columns: 23
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (12): publicaddress, caseNumber, reportedDate, beginDate, reportedDateTi...
## dbl (11): X, Y, precinct, reportedTime, beginTime, centergbsid, centerLong, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
mpd_2020 <- read_csv("Data/Police_Incidents_2020.csv")
```

```
## Warning: One or more parsing issues, see `problems()` for details
```

```
## Rows: 24136 Columns: 23
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (12): publicaddress, caseNumber, reportedDate, beginDate, reportedDateTi...
## dbl (11): X, Y, precinct, reportedTime, beginTime, centergbsid, centerLong, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
mpd_2021 <- read_csv("Data/Police_Incidents_2021.csv")
```

```
## Warning: One or more parsing issues, see `problems()` for details
```

```
## Rows: 24755 Columns: 23
## -- Column specification --------------------------------------------------------
```

```
## Delimiter: ","
## chr (12): publicaddress, caseNumber, reportedDate, beginDate, reportedDateTi...
## dbl (11): X, Y, precinct, reportedTime, beginTime, centergbsid, centerLong, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
mpd_2022 <- read_csv("Data/Police_Incidents_2022.csv")
```

```
## Warning: One or more parsing issues, see `problems()` for details

## Rows: 19555 Columns: 23
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (12): publicaddress, caseNumber, reportedDate, beginDate, reportedDateTi...
## dbl (11): X, Y, precinct, reportedTime, beginTime, centergbsid, centerLong, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
pre_pims_base <- mpd_2016 %>%
  rbind(mpd_2017) %>%
  rbind(mpd_2018a) %>%
  rename(reportedDate = ReportedDate,
         centerLong = Long,
         centerLat = Lat) %>%
  select(FID, centerLong, centerLat, Offense, reportedDate) %>%
  rename(OBJECTID = FID,
         X = centerLong,
         Y = centerLat,
         offense = Offense)

post_pims_base <- mpd_2018b %>%
  rbind(mpd_2019) %>%
  rbind(mpd_2020) %>%
  rbind(mpd_2021) %>%
  rbind(mpd_2022) %>%
  select(OBJECTID, X, Y, offense, reportedDate)

mpd <- pre_pims_base %>%
  rbind(post_pims_base)

#aggregate homicides to tract-week
homicide <- mpd %>%
  mutate(date=ymd_hms(reportedDate),
         year=isoyear(date),
         week=isoweek(date)) %>%
  filter(offense=="MURDR" & year!=2016 & year!=2015) %>% #filter homicides
  select(OBJECTID, year, week, Y, X) %>%
  st_as_sf(coords = c("X", "Y"), crs = "NAD83", remove=F) %>%
  st_join(mpls_tract) %>% #spatial join neighborhoods
  st_drop_geometry() %>%
  filter(!is.na(GEOID)) %>%
  group_by(year, week, GEOID, .drop=F) %>%
  tally(name = "homicide") %>%
  ungroup() %>%
```

```
  complete(year, week, GEOID=mpls_tract$GEOID, fill = list(homicide = 0)) %>%
  filter(!(year==2021 & week==53)) %>%
  arrange(GEOID, year, week) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  left_join(pop_denom_locf, by = c("GEOID", "year")) %>%
  mutate(homicide_rate = homicide/total_pop*1000) %>%
  st_as_sf()
```

# MPLS Murder by Week

```
#aggregate to week over tracts
homicide_week <- homicide %>%
  group_by(year, week) %>%
  summarize(homicide = sum(homicide, na.rm = T),
            total_pop = sum(total_pop, na.rm = T)) %>%
  mutate(begin_date = ISOweek2date(paste(year, paste0("W", sprintf("%02d", week)), 1,sep = "-")),
         end_date = begin_date+weeks(1)-days(1),
         homicide_rate = homicide/total_pop*1000,
         pre_post_floyd = ifelse(end_date <= as.Date("2020-05-25"), 0, 1)) %>%
  filter(end_date <= as.Date("2022-08-20"))
```

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

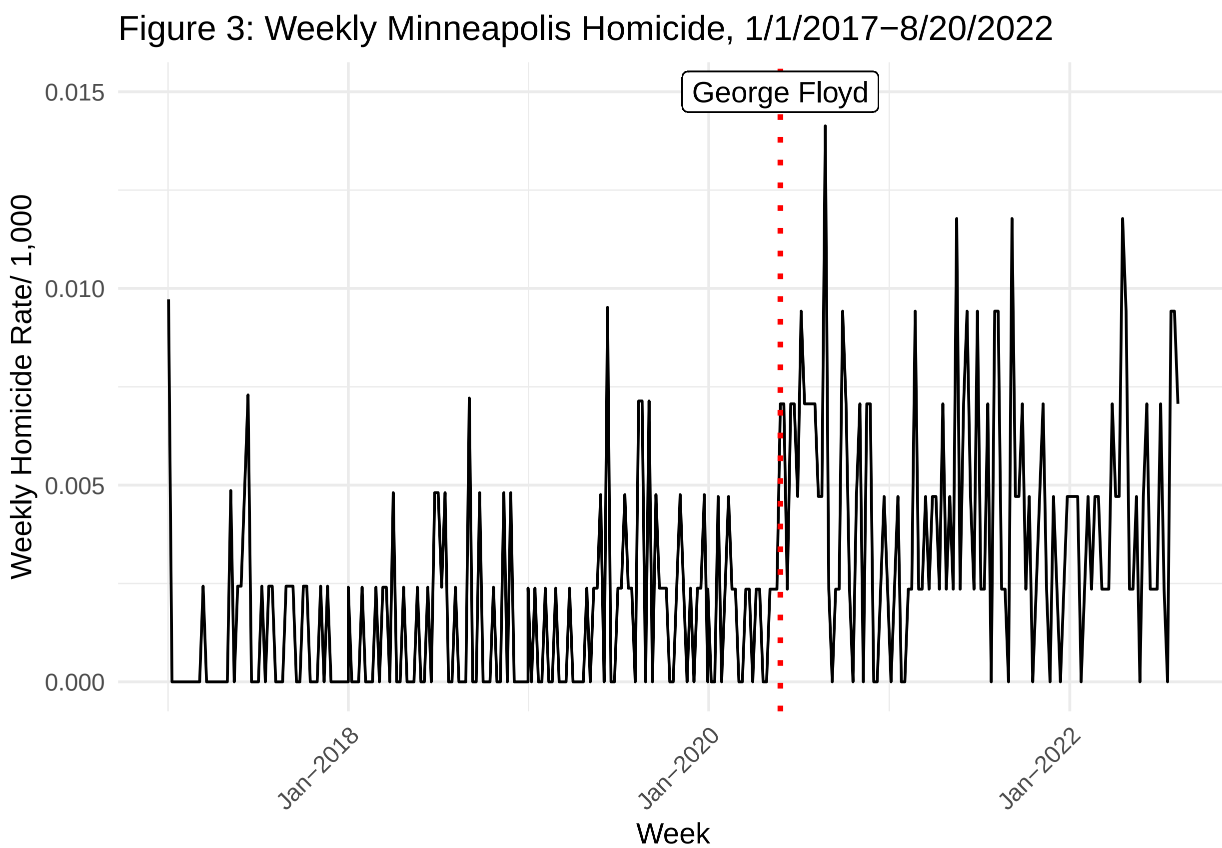
```
pre_mean <- mean(homicide_week$homicide_rate[homicide_week$pre_post_floyd==0], na.rm = T)
post_mean <- mean(homicide_week$homicide_rate[homicide_week$pre_post_floyd==1], na.rm = T)

c(pre_mean, post_mean)
```

```
## [1] 0.001462905 0.004386127
```

```
post_mean/pre_mean
```

```
## [1] 2.998231
```

```
ggplot(homicide_week)+
  geom_line(aes(x=begin_date, y=homicide_rate))+
  scale_x_date(date_labels = "%b-%Y",
               limits = c(min(homicide_week$begin_date), max(homicide_week$begin_date)))+
     labs(title = "Figure 3: Weekly Minneapolis Homicide, 1/1/2017-8/20/2022",
       x = "Week",
       y = "Weekly Homicide Rate/ 1,000")+
  geom_vline(xintercept=homicide_week$begin_date[homicide_week$year==2020 &
                                               homicide_week$week==isoweek(date("2020-05-25"))],
              linetype="dotted", color="red", size=1)+
   geom_label(aes(x=homicide_week$begin_date[homicide_week$year==2020 &
                                           homicide_week$week==isoweek(date("2020-05-25"))],
                 y=0.015),
             label = "George Floyd", show.legend = FALSE)+
  theme_minimal()+
    theme(axis.text.x=element_text(angle=45, hjust=1)) +
  theme(legend.key.size = unit(0.8, "cm"),legend.position = "bottom")
```




```r
ggsave(filename = "Car Jacking/Figures for PAA/fig3.png", bg="white", width = 10, height = 8)
```

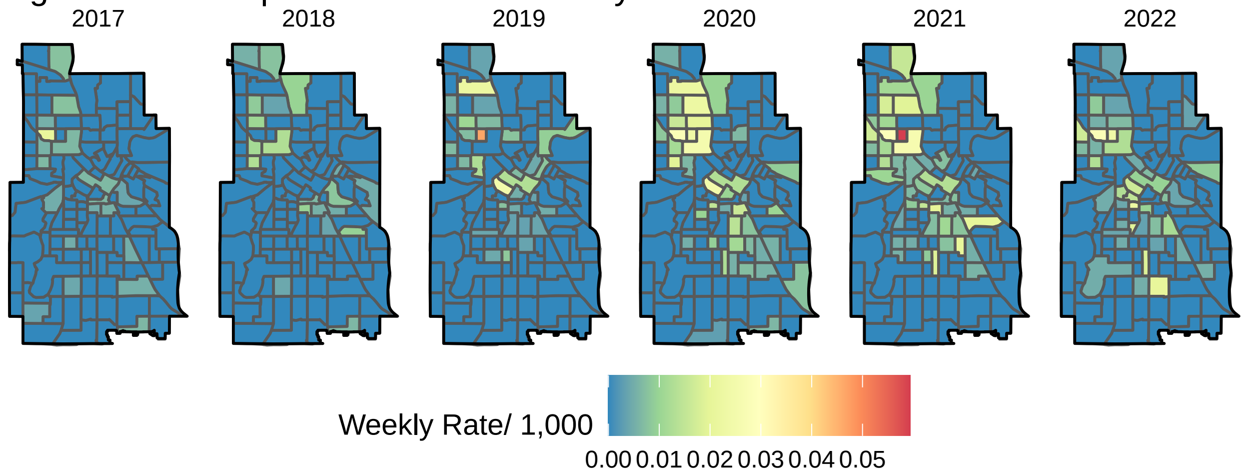
## MPLS ZCTA Murder Map - MPD Extended Data

```r
#aggregate to neighborhood-year level
homicide_tract_year <- homicide %>%
  group_by(GEOID, year) %>%
  summarize(homicide = sum(homicide, na.rm = T),
            total_pop = sum(B01001_001E, na.rm = T),
            homicide_rate = homicide/total_pop*1000) %>%
  mutate(GEOID = as.character(GEOID))
```

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

```r
ggplot() +
  geom_sf(data = homicide_tract_year, aes(geometry = geometry, fill = homicide_rate)) +
  geom_sf(data = mpls, aes(geometry = geometry), color = "black", alpha = 0)+
  facet_grid(~year)+
  scale_fill_distiller(palette = "Spectral")+
  labs(title = "Figure 4: Minneapolis Homicide Rates by Tract and Year",
       fill = "Weekly Rate/ 1,000")+
  theme_void() +
  theme(legend.key.size = unit(0.8, "cm"),legend.position = "bottom")
```

Figure 4: Minneapolis Homicide Rates by Tract and Year




```
ggsave(filename = "Car Jacking/Figures for PAA/fig4.png", bg="white", width = 10, height = 8)
```

## Dispersion of Change from 2017-2019 to 2020-2021

### Car Jacking

```
crimedispersion <- function
(data1, unitID, time1, time2, method = "match") {

  # define variables to limit build warnings
  adjusted <- Ut1 <- Ut2 <- Rt1 <- Rt2 <- chg <- pct <- NULL

  # ERROR CHECKING. Has user passed a data frame?
  if (!is.data.frame(data1)) {
    stop("The input data specified is not a data.frame object. Please fix.")
  }

  # Build a local data.frame and populate with passed arguments
  source_rows <- nrow(data1)
  df1 <- data.frame(matrix(ncol = 3, nrow = source_rows))
  colnames(df1) <- c("unit", "time1", "time2")
  df1$unit <- data1[, unitID]
  df1$time1 <- data1[, time1]
  df1$time2 <- data1[, time2]
  if (method == "remove") {
```

```r
  analysisMethod <- "remove"
} else {
  analysisMethod <- "match"
}


# ERROR CHECKING. Did user pass numeric columns where needed?
try (df1$time1 <- as.numeric(df1$time1), silent = TRUE)
try (df1$time2 <- as.numeric(df1$time2), silent = TRUE)

if (!class(df1$time1)[1] == "numeric") {
  stop("The time1 field is not a numeric object. Please fix.")
}
if (!class(df1$time2)[1] == "numeric") {
  stop("The time2 field is not a numeric object. Please fix.")
}

# MORE ERROR CHECKING:
# What if the user has NA or missing data?
# What if the crime problem is decreasing?
# Fun tasks for later...


# Set up parameters -------------------------------------------------------

# Set up initial parameters
count_Rt1 <- sum(df1$time1)
count_Rt2 <- sum(df1$time2)
chg_Rt1_Rt2 <- count_Rt2 - count_Rt1
pct_Rt1_Rt2 <- (chg_Rt1_Rt2 / count_Rt1) *100

# Add the field that has the volume of change, and order by it
df1 <- df1 %>%
  mutate (diff = time2 - time1) %>%
  mutate (diffPct = 100*(diff/time1)) %>%
  arrange(desc(diff))

# Grab some basic statistics here
numPositive <- length(which(df1$diff > 0))
numNeutral <- length(which(df1$diff == 0))
numNegative <- length(which(df1$diff < 0))


# Create the new data frame to hold the result
df2 <- data.frame(matrix(ncol =8, nrow = 0))
colnames(df2) <- c("unit", "adjusted", "Ut1", "Ut2", "Rt1", "Rt2", "chg", "pct")
df2 <- df2 %>%
  mutate(unit = as.character(unit)) %>%
  mutate(adjusted = as.numeric(adjusted)) %>%
  mutate(Ut1 = as.numeric(Ut1)) %>%
  mutate(Ut2 = as.numeric(Ut2)) %>%
  mutate(Rt1 = as.numeric(Rt1)) %>%
  mutate(Rt2 = as.numeric(Rt2)) %>%
```

```
  mutate(chg = as.numeric(chg)) %>%
  mutate(pct = as.numeric(pct))

# set up the initial row in the result data frame
df2 <- df2 %>% add_row(unit = "[ ALL AREAS ]", adjusted = 0,
                       Ut1 = 0, Ut2 = 0,
                       Rt1 = count_Rt1, Rt2 = count_Rt2,
                       chg = chg_Rt1_Rt2, pct = pct_Rt1_Rt2)

gain_from_row_removal <- row_to_remove <- NULL


# Loop through each row of the data
for (master_loop in 1:(source_rows)){

  df1 <- df1 %>%  # order the data frame
    arrange(desc(diff))

  if (analysisMethod == "match"){
    #### 'Zero change the row' approach
    count_Rt1_temp <- count_Rt1
    count_Rt2_temp <- count_Rt2 - df1$diff[master_loop]
    pct_Rt1_Rt2 <- ((count_Rt1_temp - count_Rt2_temp) / count_Rt1) *100
  }
  else { #analysisMethod == "remove"
    #### 'Remove entire row' approach, including remove t1 value
    count_Rt1_temp <- count_Rt1 - df1$time1[master_loop]
    count_Rt2_temp <- count_Rt2 - df1$time2[master_loop]
    pct_Rt1_Rt2 <- ((count_Rt1_temp - count_Rt2_temp) / count_Rt1) *100
  }

  row_to_remove <- 1  # Always row 1, but this is a legacy from
  # when I used a different approach...
  # Here, the row we are removing is
  # stored in row_to_remove

  if (analysisMethod == "remove"){
    #### Remove entire row approach
    #    This approach removes the impact of the area by subtracting
    #    both Rt1 and Rt2
    count_Rt1 <- count_Rt1 - df1$time1[row_to_remove]
    count_Rt2 <- count_Rt2 - df1$time2[row_to_remove]
    chg_Rt1_Rt2 <- count_Rt2 - count_Rt1
    pct_Rt1_Rt2 <- (chg_Rt1_Rt2 / count_Rt1) *100
    named_areas <- df1$unit[row_to_remove]
  }

  if (analysisMethod == "match"){
    #### Zero change the row approach, as if Rt2 == Rt1 in the row
    #    The best row to remove is has been exhaustively calculated
    #    Here, the row we are removing is stored in row_to_remove
    count_Rt1 <- count_Rt1
    count_Rt2 <- count_Rt2 - df1$diff[row_to_remove]
```

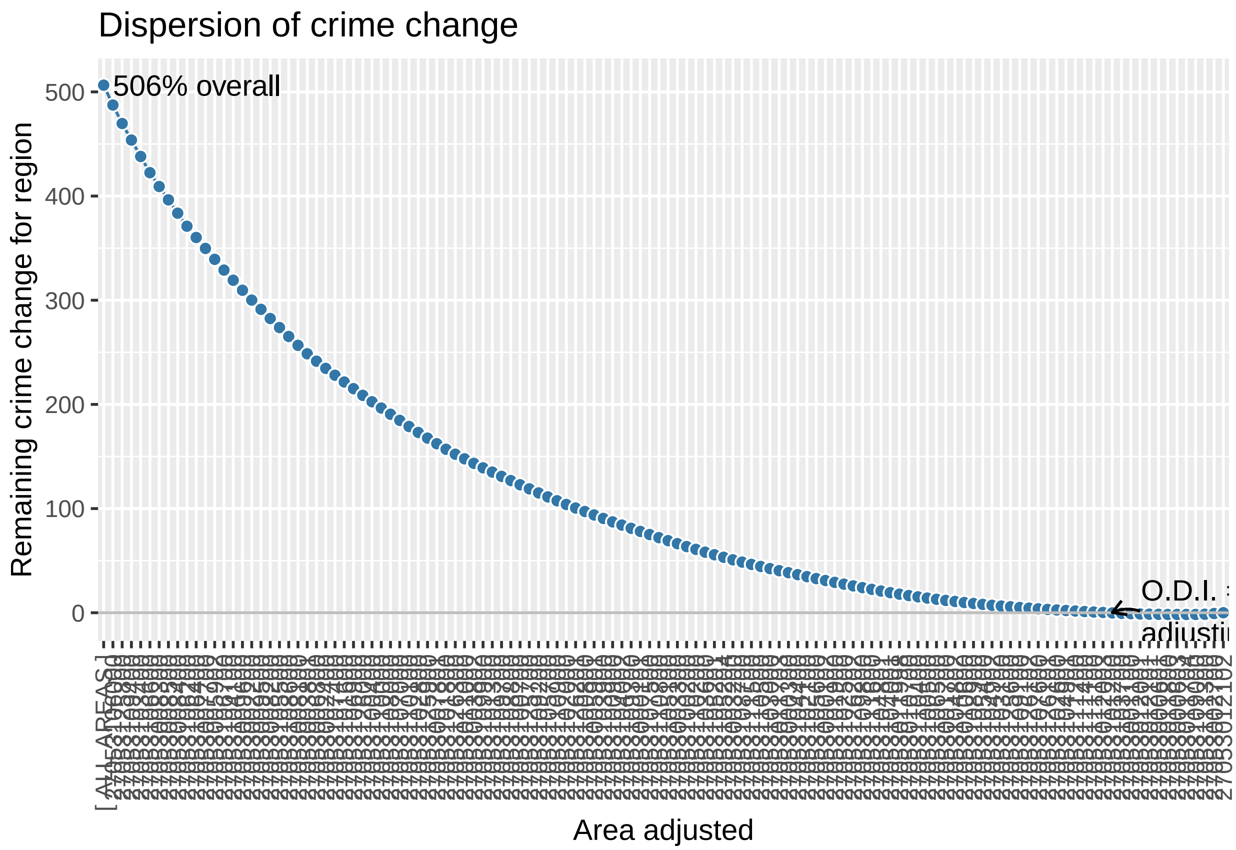
```
    chg_Rt1_Rt2 <- count_Rt2 - count_Rt1
    pct_Rt1_Rt2 <- (chg_Rt1_Rt2 / count_Rt1) *100
    named_areas <- df1$unit[row_to_remove]
  }

  # Add result to the output data frame
  df2 <- df2 %>% add_row(unit = named_areas, adjusted = master_loop,
                         Ut1 = df1$time1[row_to_remove], Ut2 = df1$time2[row_to_remove],
                         Rt1 = count_Rt1, Rt2 = count_Rt2,
                         chg = chg_Rt1_Rt2, pct = pct_Rt1_Rt2)

  # Adjust the row we just used in one of two ways:
  # 1. remove the actual row entirely
  if (analysisMethod == "remove"){
    df1 <-df1[-c(row_to_remove), ]
  }
  #2. adjust the Rt2 to match Rt1 resulting in a zero diff
  #   but show that diff as < lowest diff in the data set so that
  #   the program does not stall with too many zeros
  if (analysisMethod == "match"){
    df1$time2[row_to_remove] <- df1$time1[row_to_remove]
    df1$diff[row_to_remove] <- -999 # this should be changed to always less than
    # the lowest diff score in the data set
  }

} # end master_loop


# Calculate ODI and NCDI indices ----------------------------------------
NumContributed <- length(which(df2$chg > 0))
ODI <- NumContributed / source_rows
NCDI <- (numPositive - NumContributed) / source_rows
ODI.text <- paste("O.D.I. = ", format(ODI, digits = 3), "after \nadjusting",
                  NumContributed, "of the", source_rows, "units")

# Tidy up names for data frame --------------------------------------------

df2 <- df2 %>%
  rename(unit_t1 = Ut1, unit_t2 = Ut2, region_t1 = Rt1, region_t2 = Rt2)

# Plot --------------------------------------------------------------------

df3 <- df2
plot.adjustment <- ""
if (nrow(df3) > 151)  {
  df3 <- df3[1:151, ]
  plot.adjustment <- "Plot only shows first\n100 areas adjusted"
}


p <- ggplot(df3, aes(x=reorder(unit, adjusted), y=pct, group = 1)) +
  geom_line(color="#3277a8") +
  geom_point(shape=21, color="white", fill="#3277a8", size=2) +
```

```
    geom_hline(color="grey", yintercept=0) +
    labs(title="Dispersion of crime change",
         x ="Area adjusted", y = "Remaining crime change for region") +
    annotate(
      geom = "curve", x = NumContributed+4, y = 1.5,
      xend = NumContributed+1, yend = 0.2,
      curvature = .2, arrow = arrow(length = unit(2, "mm"))
    ) +
    annotate(geom = "text", x = NumContributed+4.1, y = 1.5,
             label = ODI.text, hjust = "left") +
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1)) +

    annotate(geom = "text", x = 2, y = df2$pct[1],
             label = paste0(format(df2$pct[1], digits = 3),"% overall"), hjust = "left") +
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))

  if (plot.adjustment != "") {
    p <- p +
      annotate(geom = "text", x = 100, y = df3$pct[1]-1, label = plot.adjustment, hjust = "right")
  }

  p


  # Create return list ------------------------------------------------------

  output <- list(df2, p, NumContributed, ODI, NCDI)
  return(output)
}


prepost_cj <- cj_exp %>%
   mutate(begin_date = ISOweek2date(paste(year, paste0("W", sprintf("%02d", week)), 1,sep = "-")),
         end_date = begin_date+weeks(1)-days(1),
         pre_post_floyd = ifelse(end_date <= as.Date("2020-05-25"), 0, 1)) %>%
  filter(end_date <= as.Date("2022-08-20")) %>%
  group_by(GEOID, pre_post_floyd) %>%
  summarize(car_jack = sum(car_jack, na.rm = T),
            total_pop = sum(total_pop, na.rm = T)) %>%
  mutate(car_jack_rate = car_jack/total_pop*1000) %>%
  select(GEOID, pre_post_floyd, car_jack, car_jack_rate) %>%
  st_drop_geometry() %>%
  pivot_wider(names_from = pre_post_floyd, values_from = c(car_jack, car_jack_rate)) %>%
  mutate(GEOID = as.character(GEOID))
```

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

```
output <- crimedispersion(as.data.frame(prepost_cj), 'GEOID', 'car_jack_rate_0', 'car_jack_rate_1')

ouput_data <- output[[1]]
n_remove <- output[[3]]
odi <- output[[4]] #ratio of n removed to n overall
ncdi <- output[[5]] #ratio of areas not contributing to overall increase but still increase to overall
```

```
output[[2]]
```




```
ggsave(filename = "Car Jacking/Figures for PAA/fig5.png", bg="white", width = 10, height = 8)
```

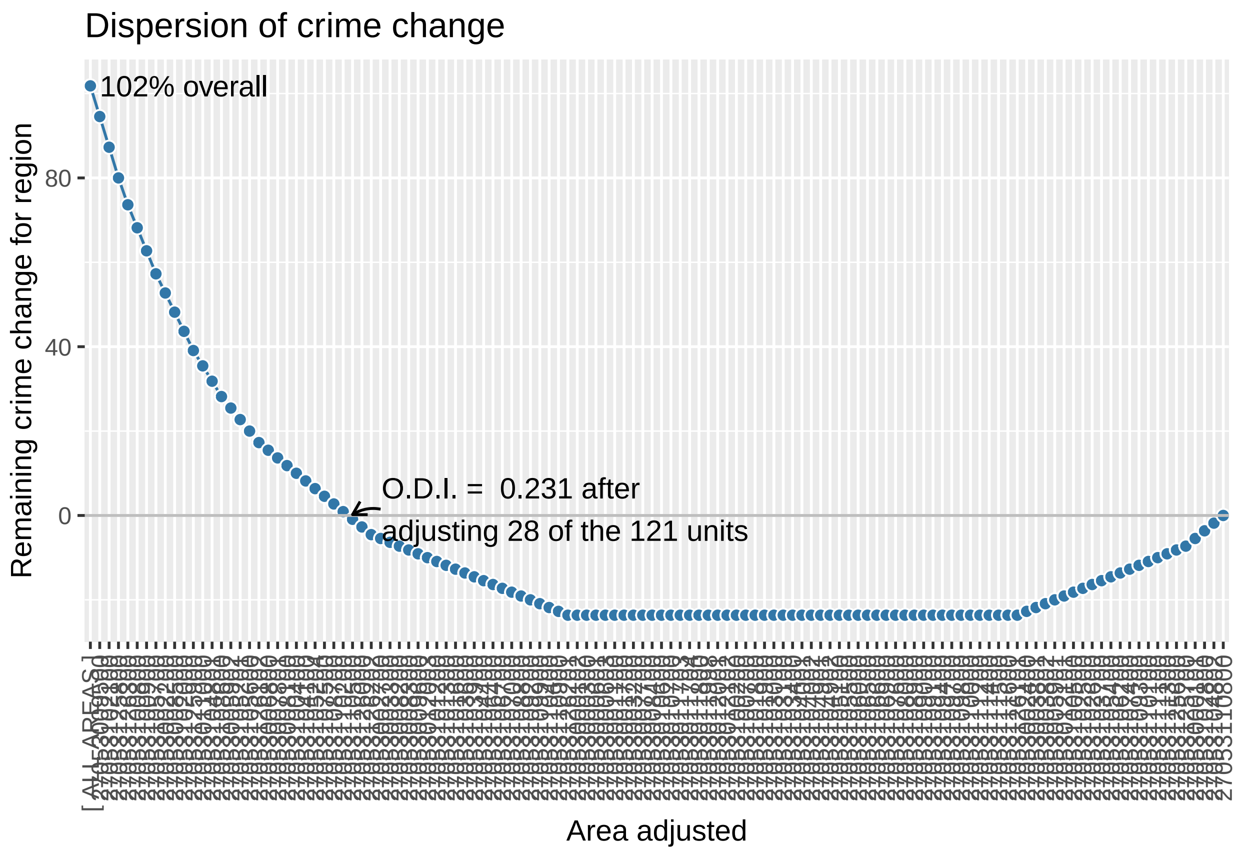
### Homicide

```
prepost_hom <- homicide %>%
 mutate(begin_date = ISOweek2date(paste(year, paste0("W", sprintf("%02d", week)), 1,sep = "-")),
         end_date = begin_date+weeks(1)-days(1),
         pre_post_floyd = ifelse(end_date <= as.Date("2020-05-25"), 0, 1)) %>%
  group_by(GEOID, pre_post_floyd) %>%
  summarize(homicide = sum(homicide, na.rm = T),
            total_pop = sum(total_pop, na.rm = T)) %>%
  mutate(homicide_rate = homicide/total_pop*1000) %>%
  st_drop_geometry() %>%
  select(GEOID, pre_post_floyd, homicide, homicide_rate) %>%
  pivot_wider(names_from = pre_post_floyd, values_from = c(homicide, homicide_rate)) %>%
  mutate(GEOID = as.character(GEOID))
```

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

```
output_homicide <- crimedispersion(as.data.frame(prepost_hom), 'GEOID', 'homicide_0', 'homicide_1')

ouput_data <- output_homicide[[1]]
n_remove <- output_homicide[[3]]
```

```r
odi <- output_homicide[[4]] #ratio of n removed to n overall
ncdi <- output_homicide[[5]] #ratio of areas not contributing to overall increase but still increase to

output_homicide[[2]]
```




```r
ggsave(filename = "Car Jacking/Figures for PAA/fig6.png", bg="white", width = 10, height = 8)
```

## Spatial Correlation *Change* in Carjackings and Homicide

### Carjacking

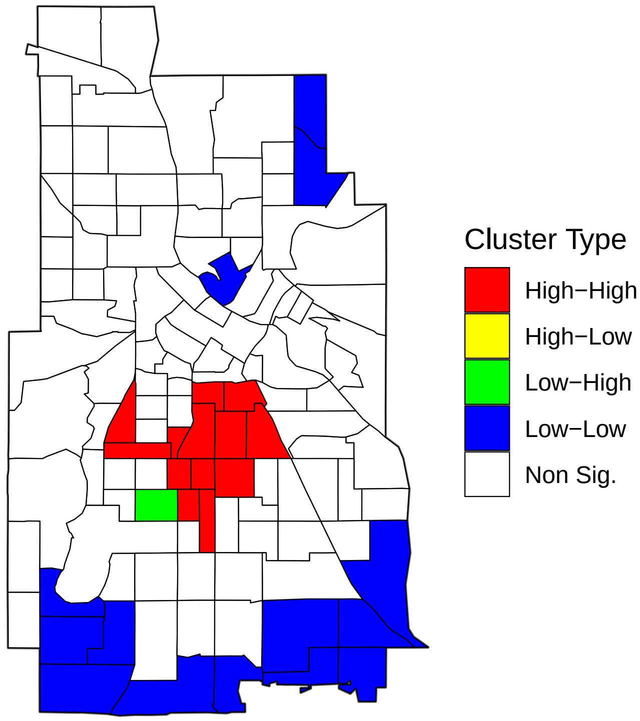
```r
library(sfdep)

cj_delta <- prepost_cj %>%
  mutate(delta = car_jack_rate_1-car_jack_rate_0,
         GEOID = as.numeric(GEOID)) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  st_as_sf()

nb <- st_contiguity(cj_delta, queen=TRUE)
wt <-  st_weights(nb, style = "W")

global_moran_test(
  cj_delta$delta,
  nb,
```

```r
  wt,
  alternative = "greater",
  randomization = TRUE)
```

```
##
##  Moran I test under randomisation
##
## data:  x
## weights: listw
##
## Moran I statistic standard deviate = 8.7057, p-value < 2.2e-16
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##       0.454267590      -0.008333333       0.002823611
```

```r
#LISA
cj_lisa <-  local_moran(cj_delta$delta,
                       nb = nb,
                       wt = wt,
                       nsim = 1000,
                       iseed = set.seed(7188)) %>%
  mutate(mean_p = ifelse(p_ii_sim <= 0.05, as.character(pysal), "Non Sig."),
         mean_p = factor(mean_p, levels = c("High-High", "High-Low", "Low-High",
                                            "Low-Low", "Non Sig.")))

cj_delta %>%
  cbind(cj_lisa) %>%
  ggplot(aes(fill = mean_p)) +
  geom_sf() +
  geom_sf(lwd = 0.2, color = "black") +
  theme_void() +
  scale_fill_manual(values = c("red", "yellow", "green", "blue","white"), drop = FALSE)+
  labs(title = "Figure 7: LISA Plot for Carjacking Change Pre/Post Police Murder",
       fill = "Cluster Type",
       caption = "Clusters significant at p < .05 with 1,000 simulations.")
```

Figure 7: LISA Plot for Carjacking Change Pre/Post Police Mu




Clusters significant at p < .05 with 1,000 simulations.

```
ggsave(filename = "Car Jacking/Figures for PAA/fig7.png", bg="white", width = 10, height = 8)
```

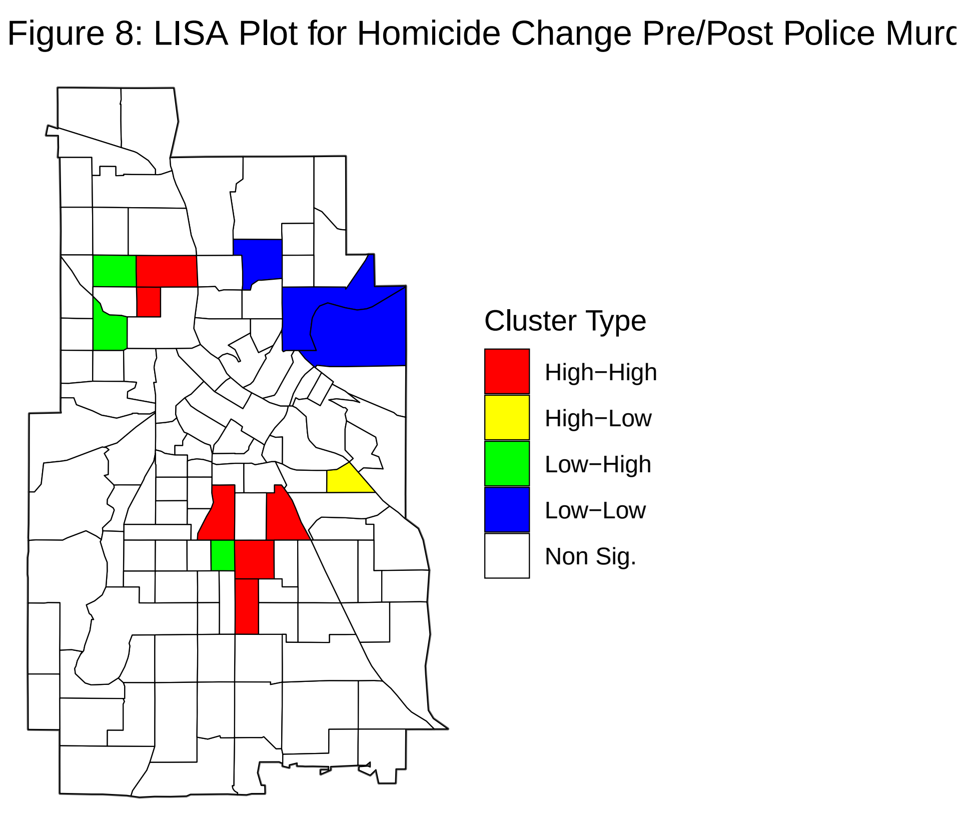
### Homicide

```
hom_delta <- prepost_hom %>%
  mutate(delta = homicide_1-homicide_0,
         GEOID = as.numeric(GEOID)) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  st_sf()


nb <- st_contiguity(hom_delta, queen=TRUE)
wt <-  st_weights(nb, style = "W")

global_moran_test(
  hom_delta$delta,
  nb,
  wt,
  alternative = "greater",
  randomization = TRUE)
```

```
##
##  Moran I test under randomisation
##
## data:  x
## weights: listw
```

```
##
## Moran I statistic standard deviate = 3.6635, p-value = 0.0001244
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##       0.185646900      -0.008333333       0.002803644
```

```
#LISA
hom_lisa <-  local_moran(hom_delta$delta,
                       nb = nb,
                       wt = wt,
                       nsim = 1000,
                       iseed = set.seed(7188)) %>%
  mutate(mean_p = ifelse(p_ii_sim <= 0.05, as.character(pysal), "Non Sig."))

hom_delta %>%
  cbind(hom_lisa) %>%
  ggplot(aes(fill = mean_p)) +
  geom_sf() +
  geom_sf(lwd = 0.2, color = "black") +
  theme_void() +
  scale_fill_manual(values = c("red", "yellow", "green","blue", "white"))+
  labs(title = "Figure 8: LISA Plot for Homicide Change Pre/Post Police Murder",
       fill = "Cluster Type",
       caption = "Clusters significant at p < .05 with 1,000 simulations.")
```



Clusters significant at p < .05 with 1,000 simulations.

```
ggsave(filename = "Car Jacking/Figures for PAA/fig8.png", bg="white", width = 10, height = 8)
```

## RE CJ Models

```
cj_exp_year_acs <- cj_exp_tract_year %>%
  left_join(acs_2020, by = c("GEOID")) %>%
  ungroup() %>%
  mutate(yearzero = year-2017,
         pov_rate_center = pov_rate-mean(pov_rate, na.rm = T),
         white_perc_center = scale(white_perc, center = T, scale = F),
         black_perc_center = scale(black_perc, center = T, scale = F),
         anyjack = ifelse(car_jack==0, 0, 1)) %>%
  drop_na()

cj_exp_prepost <- cj_exp %>%
  mutate(begin_date = ISOweek2date(paste(year, paste0("W", sprintf("%02d", week)), 1,sep = "-")),
         end_date = begin_date+weeks(1)-days(1),
         post_floyd = as.numeric(begin_date >= as.Date("2020-05-25")),
         post_floyd_3 = as.numeric(begin_date >= as.Date("2020-05-25")+months(3)),
        # stay_at_home = as.numeric(begin_date >= as.Date("2020-03-28") &
         #state_of_emerg = as.numeric(begin_date >= as.Date("2020-03-13")),
         period = factor(case_when(
           post_floyd==0 & post_floyd_3==0 ~ "Pre-Killing",
           post_floyd>=1 & post_floyd_3==0 ~ "0-3 Months Post-Killing",
           post_floyd>=1 & post_floyd_3>=1 ~ "3+ Months Post-Killing"),
           levels = c("Pre-Killing", "0-3 Months Post-Killing", "3+ Months Post-Killing")),
        GEOID = as.character(GEOID),
        anyjack = ifelse(car_jack==0, 0, 1),
        t = 1:length(car_jack_rate)) %>%
  left_join(acs_2020, by = c("GEOID")) %>%
  drop_na()

library(lme4)
library(lmerTest)


library(lavaan)

cd_model_1  <- ' cd =~ unemp_rate + pov_rate +  female_hh_rate + no_hs_dip_rate + black_perc
                  black_perc ~~ unemp_rate'

cfa_cd <- cfa(cd_model_1, data = cj_exp_prepost, std.lv = T)
modificationindices(cfa_cd)
```

```
##                lhs op            rhs      mi    epc sepc.lv sepc.all sepc.nox
## 13      unemp_rate ~~       pov_rate 776.997  6.514   6.514    0.184    0.184
## 14      unemp_rate ~~ female_hh_rate 640.565 -1.195  -1.195   -0.195   -0.195
## 15      unemp_rate ~~ no_hs_dip_rate  10.933  0.327   0.327    0.028    0.028
## 16        pov_rate ~~ female_hh_rate 414.268 -2.638  -2.638   -0.118   -0.118
## 17        pov_rate ~~ no_hs_dip_rate  62.778  2.032   2.032    0.048    0.048
## 18        pov_rate ~~     black_perc 107.800 -8.340  -8.340   -0.141   -0.141
## 19 female_hh_rate ~~ no_hs_dip_rate  88.342  0.548   0.548    0.075    0.075
```

```
## 20 female_hh_rate ~~     black_perc 703.770  5.041   5.041    0.494    0.494
## 21 no_hs_dip_rate ~~     black_perc 291.676 -7.088  -7.088   -0.367   -0.367
```

```r
summary(cfa_cd, fit.measures=TRUE, standardized = T)
```

```
## lavaan 0.6-12 ended normally after 32 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        11
##
##   Number of observations                         38040
##
## Model Test User Model:
##
##   Test statistic                              1433.656
##   Degrees of freedom                                 4
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             96858.000
##   Degrees of freedom                                10
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.985
##   Tucker-Lewis Index (TLI)                       0.963
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -600873.408
##   Loglikelihood unrestricted model (H1)    -600156.580
##
##   Akaike (AIC)                             1201768.815
##   Bayesian (BIC)                           1201862.826
##   Sample-size adjusted Bayesian (BIC)      1201827.868
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.097
##   90 Percent confidence interval - lower         0.093
##   90 Percent confidence interval - upper         0.101
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.026
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
```

```
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   cd =~
##     unemp_rate         3.520    0.023  154.568    0.000    3.520    0.749
##     pov_rate           8.350    0.067  123.785    0.000    8.350    0.591
##     female_hh_rate     2.148    0.013  162.986    0.000    2.148    0.738
##     no_hs_dip_rate     4.664    0.026  176.182    0.000    4.664    0.782
##     black_perc        17.533    0.075  234.988    0.000   17.533    0.959
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .unemp_rate ~~
##    .black_perc        -9.425    0.237  -39.771    0.000   -9.425   -0.583
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .unemp_rate         9.680    0.100   97.059    0.000    9.680    0.439
##    .pov_rate         129.663    0.973  133.264    0.000  129.663    0.650
##    .female_hh_rate     3.867    0.032  122.544    0.000    3.867    0.456
##    .no_hs_dip_rate    13.811    0.121  114.574    0.000   13.811    0.388
##    .black_perc        26.971    1.022   26.403    0.000   26.971    0.081
##     cd                 1.000                               1.000    1.000
```

```
cd_predict <- as.vector(lavPredict(cfa_cd, newdata = cj_exp_prepost))
cj_exp_prepost$conc_dis <- cd_predict


re <- lmer(car_jack_rate~t+post_floyd+post_floyd_3+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+post_floyd_3:conc_dis+
             (1|GEOID),
          data = cj_exp_prepost)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
summary(re)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## car_jack_rate ~ t + post_floyd + post_floyd_3 + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     post_floyd_3:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
## REML criterion at convergence: -96931.4
##
## Scaled residuals:
##    Min      1Q  Median      3Q     Max
## -1.138 -0.278 -0.141  0.005 32.721
```

```
##
## Random effects:
##  Groups   Name        Variance  Std.Dev.
##  GEOID    (Intercept) 6.965e-05 0.008346
##  Residual             4.536e-03 0.067351
## Number of obs: 38040, groups:  GEOID, 120
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            2.497e-02  1.075e-02  1.132e+02   2.323  0.02199 *
## t                      8.767e-08  7.878e-08  1.130e+02   1.113  0.26811
## post_floyd             1.873e-02  1.706e-03  3.792e+04  10.977  < 2e-16 ***
## post_floyd_3          -7.167e-04  1.734e-03  3.792e+04  -0.413  0.67941
## conc_dis               1.162e-03  1.335e-03  1.259e+02   0.870  0.38574
## age_19_29_perc        -1.850e-04  1.102e-04  1.130e+02  -1.680  0.09577 .
## age_30_49_perc        -1.133e-04  1.799e-04  1.130e+02  -0.629  0.53031
## age_50_69_perc        -6.536e-04  2.039e-04  1.130e+02  -3.206  0.00175 **
## age_70_plus_perc      -2.456e-04  2.458e-04  1.130e+02  -0.999  0.31990
## post_floyd:conc_dis    1.244e-02  1.735e-03  3.792e+04   7.170 7.63e-13 ***
## post_floyd_3:conc_dis -7.140e-03  1.764e-03  3.792e+04  -4.049 5.16e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) t      pst_fl pst__3 cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t            -0.021
## post_floyd   -0.011 -0.004
## post_flyd_3   0.000 -0.003 -0.913
## conc_dis     -0.724  0.050  0.000  0.000
## ag_19_29_pr -0.924 -0.052  0.000  0.000  0.679
## ag_30_49_pr -0.878 -0.108  0.000  0.000  0.590  0.747
## ag_50_69_pr -0.741 -0.125  0.001  0.000  0.603  0.719  0.444
## ag_70_pls_p -0.303 -0.036  0.000  0.000  0.191  0.278  0.282 -0.119
## pst_flyd:c_  0.000  0.000  0.000  0.000 -0.094  0.000  0.000  0.000  0.000
## pst_fly_3:_  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
##              pst_:_
## t
## post_floyd
## post_flyd_3
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
## pst_flyd:c_
## pst_fly_3:_ -0.913
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```
re_logit_cd <- glmer(anyjack ~ t+post_floyd+post_floyd_3+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+post_floyd_3:conc_dis+
             (1|GEOID),
                  data = cj_exp_prepost, family = binomial)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 3.43449 (tol = 0.002, component 1)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unider
##  - Rescale variables?;Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
summary(re_logit_cd)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: anyjack ~ t + post_floyd + post_floyd_3 + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     post_floyd_3:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
##      AIC      BIC   logLik deviance df.resid
##  10380.8  10483.3  -5178.4  10356.8    38028
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.7191 -0.2141 -0.1329 -0.0772 21.2478
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  GEOID  (Intercept) 0.4228   0.6502
## Number of obs: 38040, groups:  GEOID, 120
##
## Fixed effects:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -3.500e+00  9.026e-01  -3.877 0.000106 ***
## t                      1.337e-05  8.136e-06   1.644 0.100256
## post_floyd             1.786e+00  1.288e-01  13.866  < 2e-16 ***
## post_floyd_3           5.340e-02  1.144e-01   0.467 0.640649
## conc_dis               5.760e-01  1.181e-01   4.878 1.07e-06 ***
## age_19_29_perc        -8.335e-03  9.180e-03  -0.908 0.363887
## age_30_49_perc         1.447e-03  1.493e-02   0.097 0.922832
## age_50_69_perc        -6.457e-02  1.718e-02  -3.759 0.000171 ***
## age_70_plus_perc      -1.858e-02  2.026e-02  -0.917 0.359044
## post_floyd:conc_dis   -8.203e-02  1.031e-01  -0.795 0.426430
## post_floyd_3:conc_dis -2.557e-01  9.589e-02  -2.667 0.007655 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl pst__3 cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.096
## post_floyd  -0.040  0.010
## post_flyd_3 -0.001  0.001 -0.803
## conc_dis    -0.727  0.137  0.125  0.004
## ag_19_29_pr -0.924  0.004 -0.002  0.000  0.667
## ag_30_49_pr -0.867 -0.103 -0.002  0.000  0.570  0.749
```

```
## ag_50_69_pr -0.733 -0.096 -0.004  0.000  0.563  0.718  0.446
## ag_70_pls_p -0.276 -0.021 -0.004 -0.003  0.164  0.258  0.263 -0.141
## pst_flyd:c_  0.020 -0.008 -0.450  0.347 -0.223  0.001  0.002  0.001  0.005
## pst_fly_3:_  0.002 -0.017  0.329 -0.408 -0.013  0.001  0.002  0.001  0.009
##             pst_:_
## t
## post_floyd
## post_flyd_3
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
## pst_flyd:c_
## pst_fly_3:_ -0.802
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
## optimizer (Nelder_Mead) convergence code: 0 (OK)
## Model failed to converge with max|grad| = 3.43449 (tol = 0.002, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
#build in police covariates
#what other covariates do we need here?
  #crude model - no post-treatment control
#businesses - crime generators
#percent single males
#percent "isolated" youth
#similar story with homicide?
#FE models


cj_exp_prepost <- cj_exp_prepost %>%
  mutate(GEOID = as.numeric(GEOID)) %>%
  left_join(homicide, by = c("GEOID", "year","week")) %>%
  mutate(anyhom = ifelse(homicide==0, 0, 1))

re_homicide <- lmer(homicide_rate~t+post_floyd+post_floyd_3+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+post_floyd_3:conc_dis+
             (1|GEOID),
          data = cj_exp_prepost)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
summary(re_homicide)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
```

```
## homicide_rate ~ t + post_floyd + post_floyd_3 + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     post_floyd_3:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
## REML criterion at convergence: -156349.3
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -1.251 -0.111 -0.039 -0.011 39.180
##
## Random effects:
##  Groups   Name        Variance  Std.Dev.
##  GEOID    (Intercept) 7.671e-06 0.00277
##  Residual             9.523e-04 0.03086
## Number of obs: 38040, groups:  GEOID, 120
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            1.701e-03  3.834e-03  1.133e+02   0.444  0.65817
## t                      1.817e-08  2.809e-08  1.130e+02   0.647  0.51893
## post_floyd             5.685e-03  7.816e-04  3.792e+04   7.273 3.58e-13 ***
## post_floyd_3          -3.543e-03  7.946e-04  3.792e+04  -4.458 8.28e-06 ***
## conc_dis               1.477e-03  4.841e-04  1.347e+02   3.050  0.00275 **
## age_19_29_perc         6.788e-06  3.928e-05  1.130e+02   0.173  0.86310
## age_30_49_perc        -3.782e-05  6.416e-05  1.130e+02  -0.590  0.55669
## age_50_69_perc         7.990e-05  7.269e-05  1.130e+02   1.099  0.27404
## age_70_plus_perc      -1.741e-04  8.764e-05  1.130e+02  -1.986  0.04944 *
## post_floyd:conc_dis    6.393e-03  7.949e-04  3.792e+04   8.042 9.06e-16 ***
## post_floyd_3:conc_dis -4.636e-03  8.080e-04  3.792e+04  -5.737 9.70e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl pst__3 cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.021
## post_floyd  -0.015 -0.003
## post_flyd_3  0.000 -0.002 -0.913
## conc_dis    -0.712  0.049  0.000  0.000
## ag_19_29_pr -0.923 -0.052  0.000  0.000  0.667
## ag_30_49_pr -0.878 -0.108  0.000  0.000  0.580  0.747
## ag_50_69_pr -0.741 -0.125  0.000  0.000  0.593  0.719  0.444
## ag_70_pls_p -0.303 -0.036  0.000  0.000  0.188  0.278  0.282 -0.119
## pst_flyd:c_  0.000  0.000  0.000  0.000 -0.118  0.000  0.000  0.000  0.000
## pst_fly_3:_  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
##             pst_:_
## t
## post_floyd
## post_flyd_3
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
```

```
## pst_flyd:c_
## pst_fly_3:_ -0.913
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```
re_logit_cd_homicide <- glmer(anyhom ~ t+post_floyd+post_floyd_3+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+post_floyd_3:conc_dis+
             (1|GEOID),
                  data = cj_exp_prepost, family = binomial)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## unable to evaluate scaled gradient

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge: degenerate Hessian with 1 negative eigenvalues
```

```
summary(re_logit_cd)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: anyjack ~ t + post_floyd + post_floyd_3 + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     post_floyd_3:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
##      AIC      BIC   logLik deviance df.resid
##  10380.8  10483.3  -5178.4  10356.8    38028
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.7191 -0.2141 -0.1329 -0.0772 21.2478
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  GEOID  (Intercept) 0.4228   0.6502
## Number of obs: 38040, groups:  GEOID, 120
##
## Fixed effects:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -3.500e+00  9.026e-01  -3.877 0.000106 ***
## t                      1.337e-05  8.136e-06   1.644 0.100256
## post_floyd             1.786e+00  1.288e-01  13.866  < 2e-16 ***
## post_floyd_3           5.340e-02  1.144e-01   0.467 0.640649
## conc_dis               5.760e-01  1.181e-01   4.878 1.07e-06 ***
## age_19_29_perc        -8.335e-03  9.180e-03  -0.908 0.363887
## age_30_49_perc         1.447e-03  1.493e-02   0.097 0.922832
## age_50_69_perc        -6.457e-02  1.718e-02  -3.759 0.000171 ***
## age_70_plus_perc      -1.858e-02  2.026e-02  -0.917 0.359044
## post_floyd:conc_dis   -8.203e-02  1.031e-01  -0.795 0.426430
## post_floyd_3:conc_dis -2.557e-01  9.589e-02  -2.667 0.007655 **
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl pst__3 cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.096
## post_floyd  -0.040  0.010
## post_flyd_3 -0.001  0.001 -0.803
## conc_dis    -0.727  0.137  0.125  0.004
## ag_19_29_pr -0.924  0.004 -0.002  0.000  0.667
## ag_30_49_pr -0.867 -0.103 -0.002  0.000  0.570  0.749
## ag_50_69_pr -0.733 -0.096 -0.004  0.000  0.563  0.718  0.446
## ag_70_pls_p -0.276 -0.021 -0.004 -0.003  0.164  0.258  0.263 -0.141
## pst_flyd:c_  0.020 -0.008 -0.450  0.347 -0.223  0.001  0.002  0.001  0.005
## pst_fly_3:_  0.002 -0.017  0.329 -0.408 -0.013  0.001  0.002  0.001  0.009
##             pst_:_
## t
## post_floyd
## post_flyd_3
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
## pst_flyd:c_
## pst_fly_3:_ -0.802
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
## optimizer (Nelder_Mead) convergence code: 0 (OK)
## Model failed to converge with max|grad| = 3.43449 (tol = 0.002, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
class(re) <- "lmerMod"
class(re_logit_cd) <- "lmerMod"

stargazer(re, re_logit_cd,
          title = "Interrupted Time Series Models of Carjackings, MPLS 2017-2022",
          covariate.labels = c("T", "Post-Killing", "Post-Killing 3 Months",
                               "Conc. Dis.", "Age 19-29", "Age 30-49",
                               "Age 50-69", "Age 70+",
                               "Post-Killing X Conc. Dis.",
                               "Post-Killing 3 Months X Conc. Dis."),
          header = F,
          dep.var.caption = "Carjacking",
          dep.var.labels = c("Rate per 1,000", "Any Carjacking"),
          model.names = FALSE,
          column.labels = c("RE HLM","RE Logit"),
          report = "vcs",
          ci=TRUE,
          ci.level=0.95,
          ci.separator = "|",
          notes = "95\\% Confidence Intervals in parentheses",
```

```
single.row = F,
omit.stat = c("adj.rsq", "aic", "bic"),
#star.cutoffs = c(.05, .01, .001), star.char = c("*","**","***"),
add.lines = list(c("SD(Tract)", .008, .650),
                 c("SD(Residual)",  .067, "")),
notes.append = F)
```

Table 1: Interrupted Time Series Models of Carjackings, MPLS 2017-2022

| | Carjacking | |
|---|---|---|
| | Rate per 1,000<br>RE HLM | Any Carjacking<br>RE Logit |
| | (1) | (2) |
| T | 0.00000<br>(−0.00000\|0.00000) | 0.00001<br>(−0.00000\|0.00003) |
| Post-Killing | 0.019<br>(0.015\|0.022) | 1.786<br>(1.533\|2.038) |
| Post-Killing 3 Months | −0.001<br>(−0.004\|0.003) | 0.053<br>(−0.171\|0.278) |
| Conc. Dis. | 0.001<br>(−0.001\|0.004) | 0.576<br>(0.345\|0.807) |
| Age 19-29 | −0.0002<br>(−0.0004\|0.00003) | −0.008<br>(−0.026\|0.010) |
| Age 30-49 | −0.0001<br>(−0.0005\|0.0002) | 0.001<br>(−0.028\|0.031) |
| Age 50-69 | −0.001<br>(−0.001\|−0.0003) | −0.065<br>(−0.098\|−0.031) |
| Age 70+ | −0.0002<br>(−0.001\|0.0002) | −0.019<br>(−0.058\|0.021) |
| Post-Killing X Conc. Dis. | 0.012<br>(0.009\|0.016) | −0.082<br>(−0.284\|0.120) |
| Post-Killing 3 Months X Conc. Dis. | −0.007<br>(−0.011\|−0.004) | −0.256<br>(−0.444\|−0.068) |
| Constant | 0.025<br>(0.004\|0.046) | −3.500<br>(−5.269\|−1.731) |
| SD(Tract) | 0.008 | 0.65 |
| SD(Residual) | 0.067 | |
| Observations | 38,040 | 38,040 |
| Log Likelihood | 48,465.680 | −5,178.390 |
| *Note:* | | 95% Confidence Intervals in parentheses |

## RE CJ Models

```
class(re_homicide) <- "lmerMod"
class(re_logit_cd_homicide) <- "lmerMod"

stargazer(re_homicide, re_logit_cd_homicide,
          title = "Interrupted Time Series Models of Homicide, MPLS 2017-2022",
          covariate.labels = c("T", "Post-Killing", "Post-Killing 3 Months",
                               "Conc. Dis.", "Age 19-29", "Age 30-49",
                               "Age 50-69", "Age 70+",
                               "Post-Killing X Conc. Dis.",
                               "Post-Killing 3 Months X Conc. Dis."),
          header = F,
          dep.var.caption = "Homicide",
          dep.var.labels = c("Rate per 1,000", "Any Homicide"),
          model.names = FALSE,
          column.labels = c("RE HLM","RE Logit"),
          report = "vcs",
          ci=TRUE,
          ci.level=0.95,
          ci.separator = "|",
          notes = "95\\% Confidence Intervals in parentheses",
          single.row = F,
          omit.stat = c("adj.rsq", "aic", "bic"),
          #star.cutoffs = c(.05, .01, .001), star.char = c("*","**","***"),
          add.lines = list(c("SD(Tract)", .003, .031),
                           c("SD(Residual)", .065, "-")),
          notes.append = F)
```

Table 2: Interrupted Time Series Models of Homicide, MPLS 2017-2022

| | Homicide | |
|---|---|---|
| | Rate per 1,000<br>RE HLM | Any Homicide<br>RE Logit |
| | (1) | (2) |
| T | 0.00000<br>(−0.00000\|0.00000) | 0.00002<br>(−0.00000\|0.00004) |
| Post-Killing | 0.006<br>(0.004\|0.007) | 1.449<br>(0.966\|1.932) |
| Post-Killing 3 Months | −0.004<br>(−0.005\|−0.002) | −0.573<br>(−1.033\|−0.112) |
| Conc. Dis. | 0.001<br>(0.001\|0.002) | 0.915<br>(0.566\|1.264) |
| Age 19-29 | 0.00001<br>(−0.0001\|0.0001) | 0.016<br>(−0.011\|0.043) |
| Age 30-49 | −0.00004<br>(−0.0002\|0.0001) | 0.012<br>(−0.032\|0.056) |
| Age 50-69 | 0.0001<br>(−0.0001\|0.0002) | 0.017<br>(−0.035\|0.070) |
| Age 70+ | −0.0002<br>(−0.0003\|−0.00000) | −0.043<br>(−0.107\|0.020) |
| Post-Killing X Conc. Dis. | 0.006<br>(0.005\|0.008) | 0.145<br>(−0.175\|0.465) |
| Post-Killing 3 Months X Conc. Dis. | −0.005<br>(−0.006\|−0.003) | −0.182<br>(−0.487\|0.123) |
| Constant | 0.002<br>(−0.006\|0.009) | −7.125<br>(−9.722\|−4.528) |
| SD(Tract) | 0.003 | 0.031 |
| SD(Residual) | 0.065 | - |
| Observations | 38,040 | 38,040 |
| Log Likelihood | 78,174.660 | −1,661.554 |
| *Note:* | 95% Confidence Intervals in parentheses | |