Car Jacking MPLS - Tract

Ryan Larson

2022-12-20

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 and Denominators

```
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 sessions

##   |                                                                              |
```

```
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 sessions

##   |                                                                              |
```

```
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 sessions

##   |                                                                              |
```

```
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 sessions
```

```
library(tigris)
```

```
## Warning: package 'tigris' was built under R version 4.2.2

## 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) %>%
```

```
  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
```

```
# 2020 Census 18+ Denominator
dc2020 <- get_decennial(
  geography = "tract",
  variables = c("P3_001N"),
  year = 2020,
  state = "MN",
  county = "Hennepin",
  geometry = F) %>%
  mutate(GEOID = is.numeric(GEOID)) %>%
  rename(total_pop = value) %>%
  select(-GEOID)
```

```
## Getting data from the 2020 decennial Census

## Using the PL 94-171 Redistricting Data summary file

## Note: 2020 decennial Census data use differential privacy, a technique that
## introduces errors into data to preserve respondent confidentiality.
## i Small counts should be interpreted with caution.
## i See https://www.census.gov/library/fact-sheets/2021/protecting-the-confidentiality-of-the-2020-cens
## This message is displayed once per session.
```

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(dc2020, by = c("NAME")) %>%
  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")) %>%
  ungroup() %>%
  mutate(csma = forecast::ma(car_jack_rate, order=5, centre=TRUE),
         tsma = TTR::SMA(car_jack_rate, n=5))
```

```
## `summarise()` has grouped output by 'year'. You can override using the
## `.groups` argument.
## Registered S3 method overwritten by 'quantmod': method from as.zoo.data.frame
## zoo
```

```
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] 0.004835884 0.030361407
```

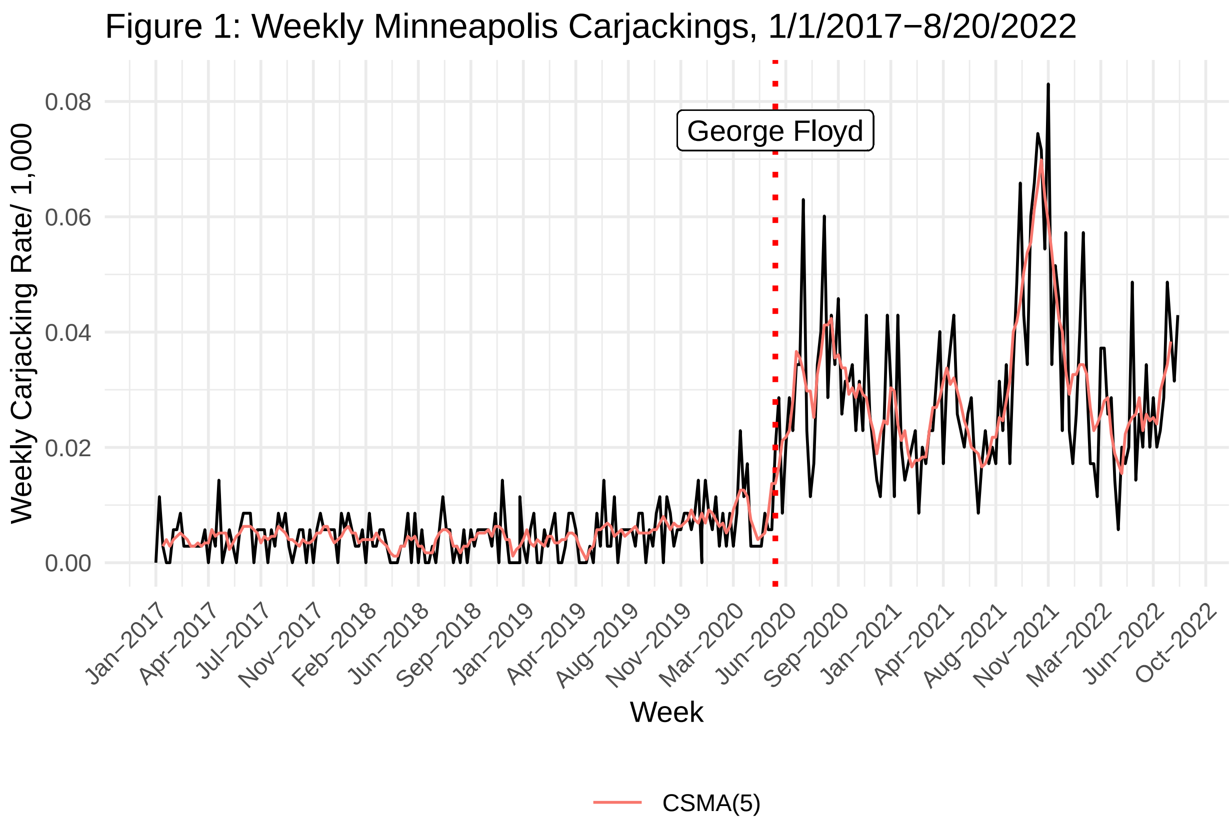
```
post_mean/pre_mean
```

```
## [1] 6.278358
```

```
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=0.075),
             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",
      color = NULL)+
  geom_line(aes(x=begin_date, y=csma, color = "CSMA(5)"))+
```

```
  theme_minimal()+
    theme(axis.text.x=element_text(angle=45, hjust=1))  +
  theme(legend.key.size = unit(0.8, "cm"),legend.position = "bottom")
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.

## Warning: Use of `cj_exp_week$begin_date` is discouraged.
## i Use `begin_date` instead.

## Warning: Use of `cj_exp_week$year` is discouraged.
## i Use `year` instead.

## Warning: Use of `cj_exp_week$week` is discouraged.
## i Use `week` instead.

## Warning: Removed 4 rows containing missing values (`geom_line()`).
```




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

```
## Warning: Use of `cj_exp_week$begin_date` is discouraged.
## i Use `begin_date` instead.

## Warning: Use of `cj_exp_week$year` is discouraged.
## i Use `year` instead.

## Warning: Use of `cj_exp_week$week` is discouraged.
## i Use `week` instead.

## Warning: Removed 4 rows containing missing values (`geom_line()`).
```

Structural Change in Carjacking

```r
library(strucchange)
```

```
## Warning: package 'strucchange' was built under R version 4.2.2

## Loading required package: sandwich

## Warning: package 'sandwich' was built under R version 4.2.2

##
## Attaching package: 'strucchange'

## The following object is masked from 'package:stringr':
##
##     boundary
```

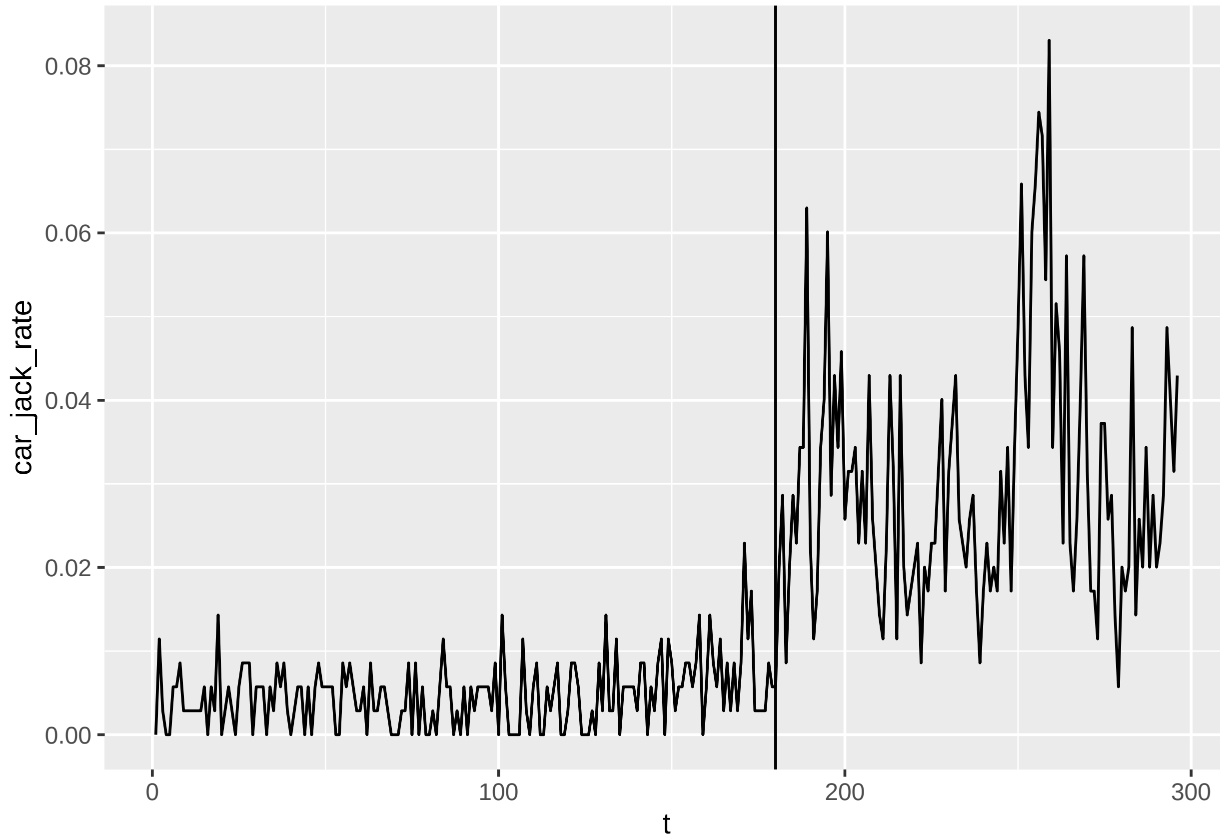
```r
cj_exp_week <- cj_exp_week %>%
  ungroup() %>%
  mutate(t = row_number())

sctest(cj_exp_week$car_jack_rate~cj_exp_week$t,
       type = "Chow",
       point = 180)
```

```
##
##  Chow test
##
## data:  cj_exp_week$car_jack_rate ~ cj_exp_week$t
## F = 49.567, p-value < 2.2e-16
```

```r
breakpoints(car_jack_rate~t,
            data = cj_exp_week,
            breaks = 1)
```

```
##
##   Optimal 2-segment partition:
##
## Call:
## breakpoints.formula(formula = car_jack_rate ~ t, breaks = 1,
##     data = cj_exp_week)
##
## Breakpoints at observation number:
## 180
##
## Corresponding to breakdates:
## 0.6081081
```

```r
ggplot(cj_exp_week)+
  geom_line(aes(x=t, y=car_jack_rate))+
  geom_vline(aes(xintercept = 180))
```



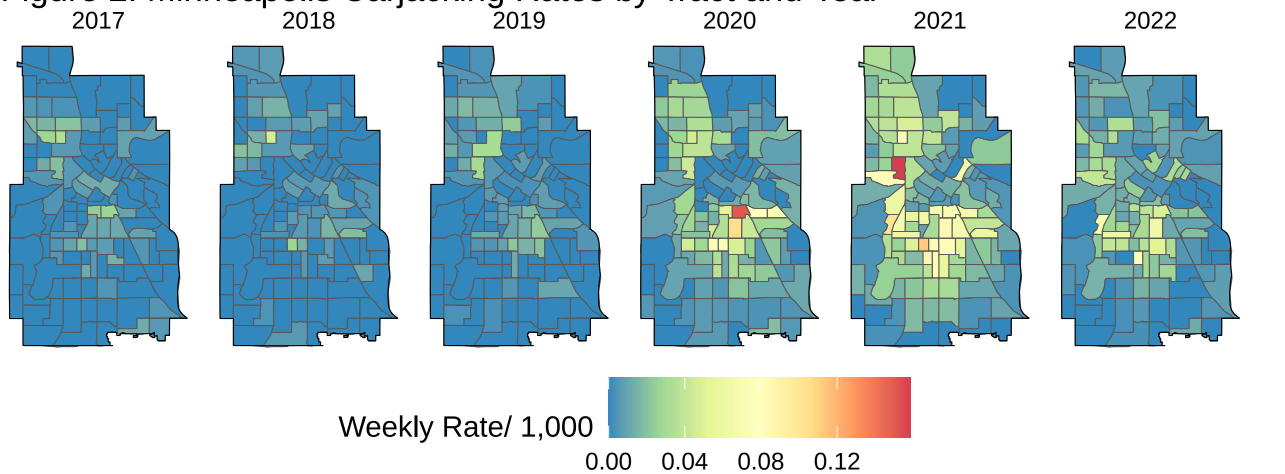
MPLS ZCTA Carjackings Map - MPD Extended Data

```
#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




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

MPLS Murder (Crime Incidents) Data

```
#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.
```

```
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, call `problems()` on your data frame for details,
## e.g.:
##   dat <- vroom(...)
##   problems(dat)

## 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, call `problems()` on your data frame for details,
## e.g.:
##   dat <- vroom(...)
##   problems(dat)

## 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, call `problems()` on your data frame for details,
## e.g.:
##   dat <- vroom(...)
##   problems(dat)

## 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.
```

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

```
## Warning: One or more parsing issues, call `problems()` on your data frame for details,
## e.g.:
##   dat <- vroom(...)
##   problems(dat)

## 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.
```

```r
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 %>%
```

```r
  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(dc2020, by = c("NAME")) %>%
  mutate(homicide_rate = homicide/total_pop*1000) %>%
  st_as_sf()
```

MPLS Murder by Week

```r
#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")) %>%
  ungroup() %>%
  mutate(csma = forecast::ma(homicide_rate, order=5,centre=TRUE),
         tsma = TTR::SMA(homicide_rate, n=5))
```

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

```r
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] 0.001749826 0.005331759
```

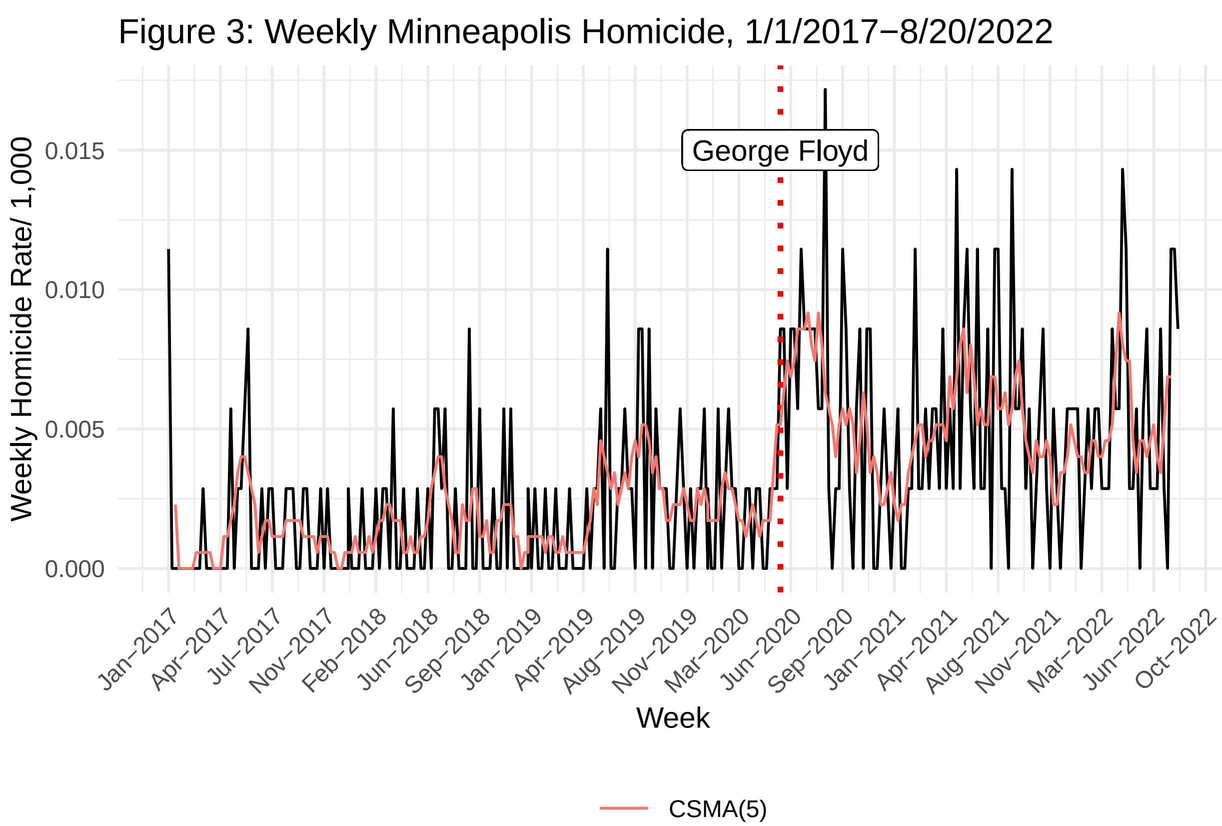
```r
post_mean/pre_mean
```

```
## [1] 3.047022
```

```r
ggplot(homicide_week)+
  geom_line(aes(x=begin_date, y=homicide_rate))+
 scale_x_date(date_labels = "%b-%Y", date_breaks = "15 weeks",
               limits = c(min(homicide_week$begin_date), max(homicide_week$begin_date)))+
```

```r
   labs(title = "Figure 3: Weekly Minneapolis Homicide, 1/1/2017-8/20/2022",
     x = "Week",
     y = "Weekly Homicide Rate/ 1,000",
     color = NULL)+
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()+
geom_line(aes(x=begin_date, y=csma, color = "CSMA(5)"))+
theme(axis.text.x=element_text(angle=45, hjust=1)) +
theme(legend.key.size = unit(0.8, "cm"),legend.position = "bottom")
```

```
## Warning: Use of `homicide_week$begin_date` is discouraged.
## i Use `begin_date` instead.

## Warning: Use of `homicide_week$year` is discouraged.
## i Use `year` instead.

## Warning: Use of `homicide_week$week` is discouraged.
## i Use `week` instead.

## Warning: Removed 4 rows containing missing values (`geom_line()`).
```



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

```
## Warning: Use of `homicide_week$begin_date` is discouraged.
## i Use `begin_date` instead.

## Warning: Use of `homicide_week$year` is discouraged.
## i Use `year` instead.

## Warning: Use of `homicide_week$week` is discouraged.
## i Use `week` instead.

## Warning: Removed 4 rows containing missing values (`geom_line()`).
```

Structural Change in Carjacking

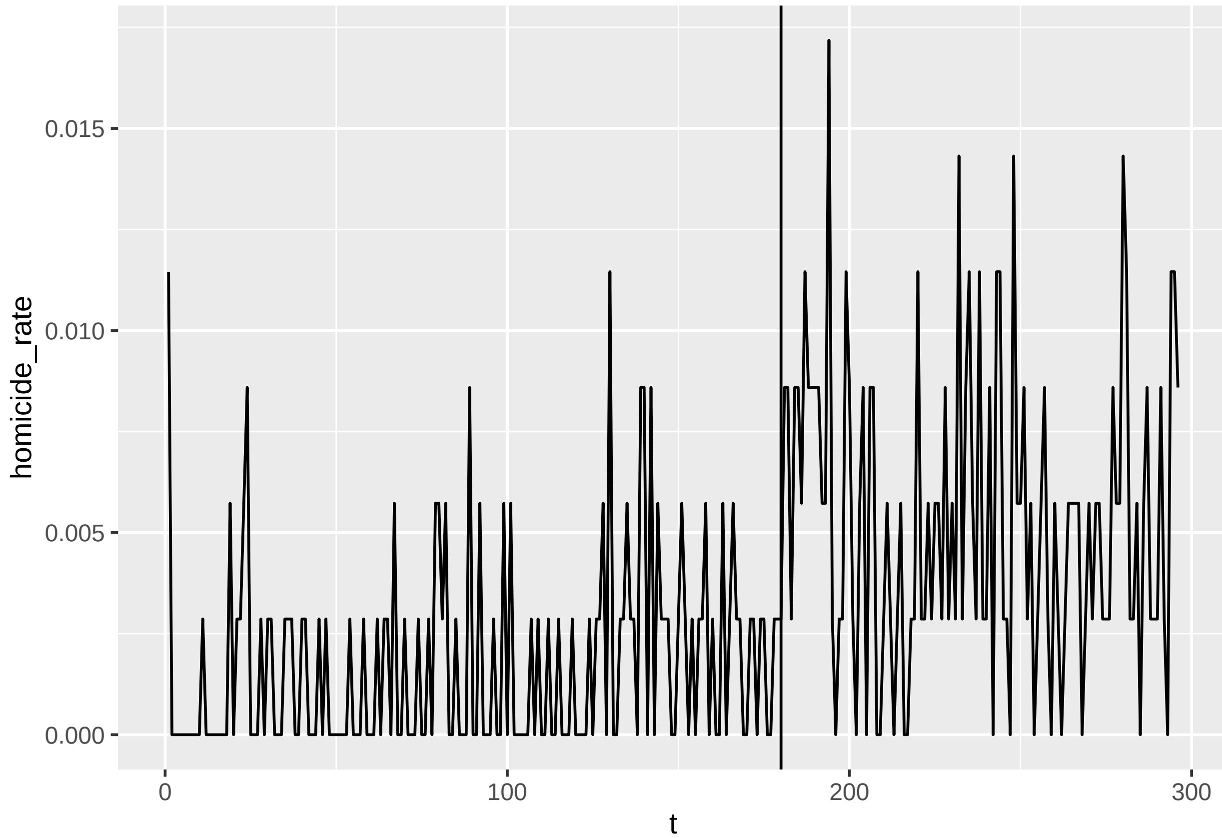
```
homicide_week <- homicide_week %>%
  ungroup() %>%
  mutate(t = row_number())

sctest(homicide_week$homicide_rate~homicide_week$t,
       type = "Chow",
       point = 180)
```

```
##
##  Chow test
##
## data:  homicide_week$homicide_rate ~ homicide_week$t
## F = 10.643, p-value = 3.454e-05
```

```
breakpoints(homicide_rate~t,
            data = homicide_week,
            breaks = 1)
```

```
##
##   Optimal 2-segment partition:
##
## Call:
## breakpoints.formula(formula = homicide_rate ~ t, breaks = 1,
##     data = homicide_week)
##
## Breakpoints at observation number:
## 180
##
## Corresponding to breakdates:
## 0.6081081
```

```
ggplot(homicide_week)+
  geom_line(aes(x=t, y=homicide_rate))+
  geom_vline(aes(xintercept = 180))
```



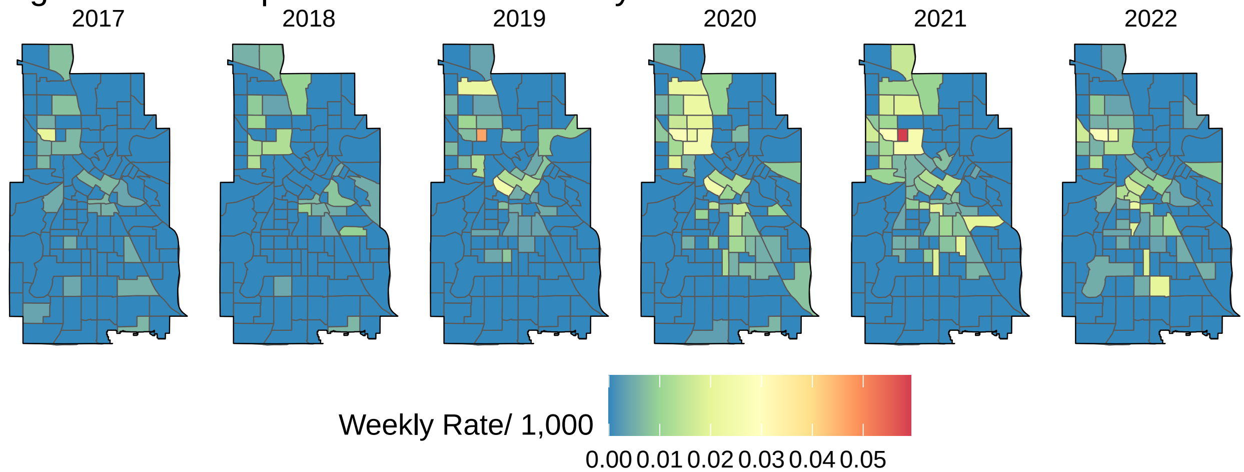
MPLS ZCTA Murder Map - MPD Extended Data

```
#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.
```

```
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]
```

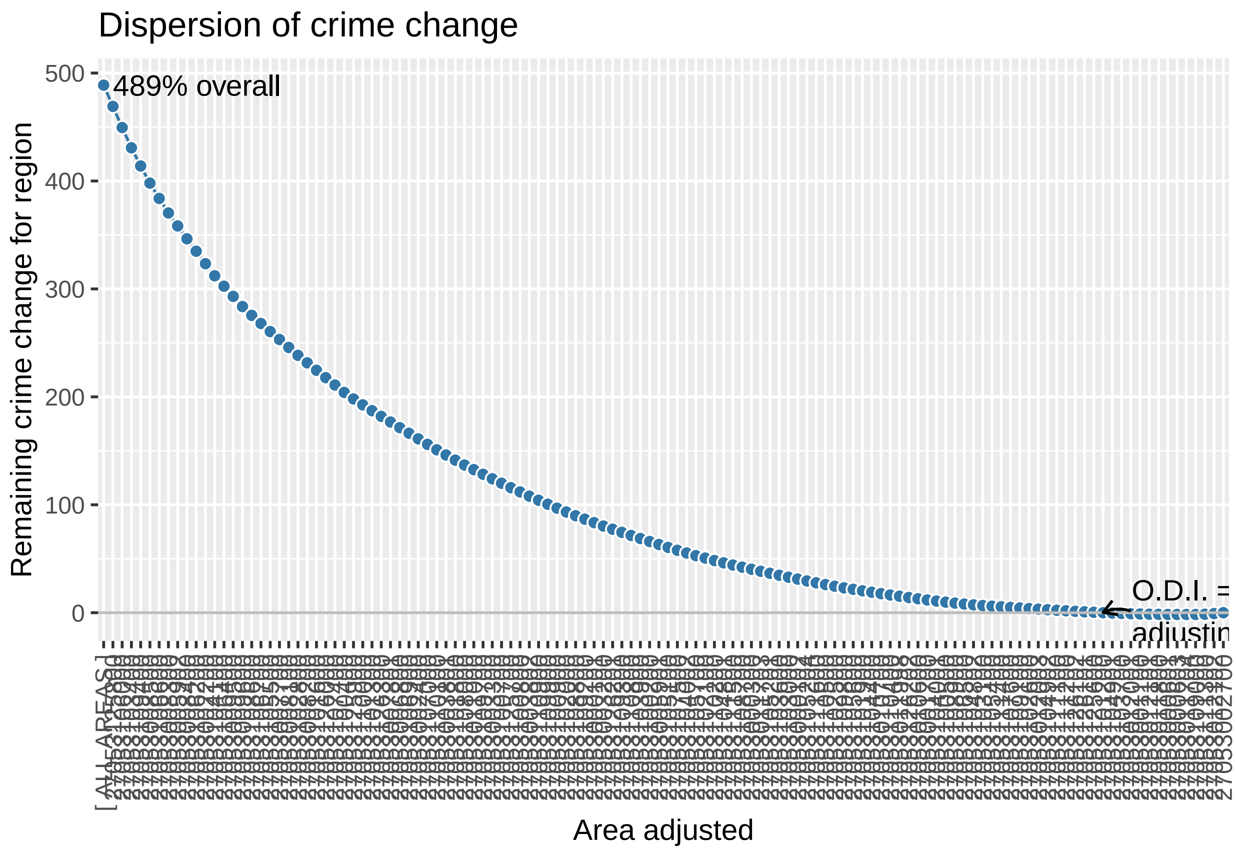
```
    chg_Rt1_Rt2 <- count_Rt2 - count_Rt1
    pct_Rt1_Rt2 <- (chg_Rt1_Rt2 / count_Rt1) *100
    named_areas <- df1$unit[row_to_remove]
  }

  # 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) +
```

```r
    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.
```

```r
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)
```

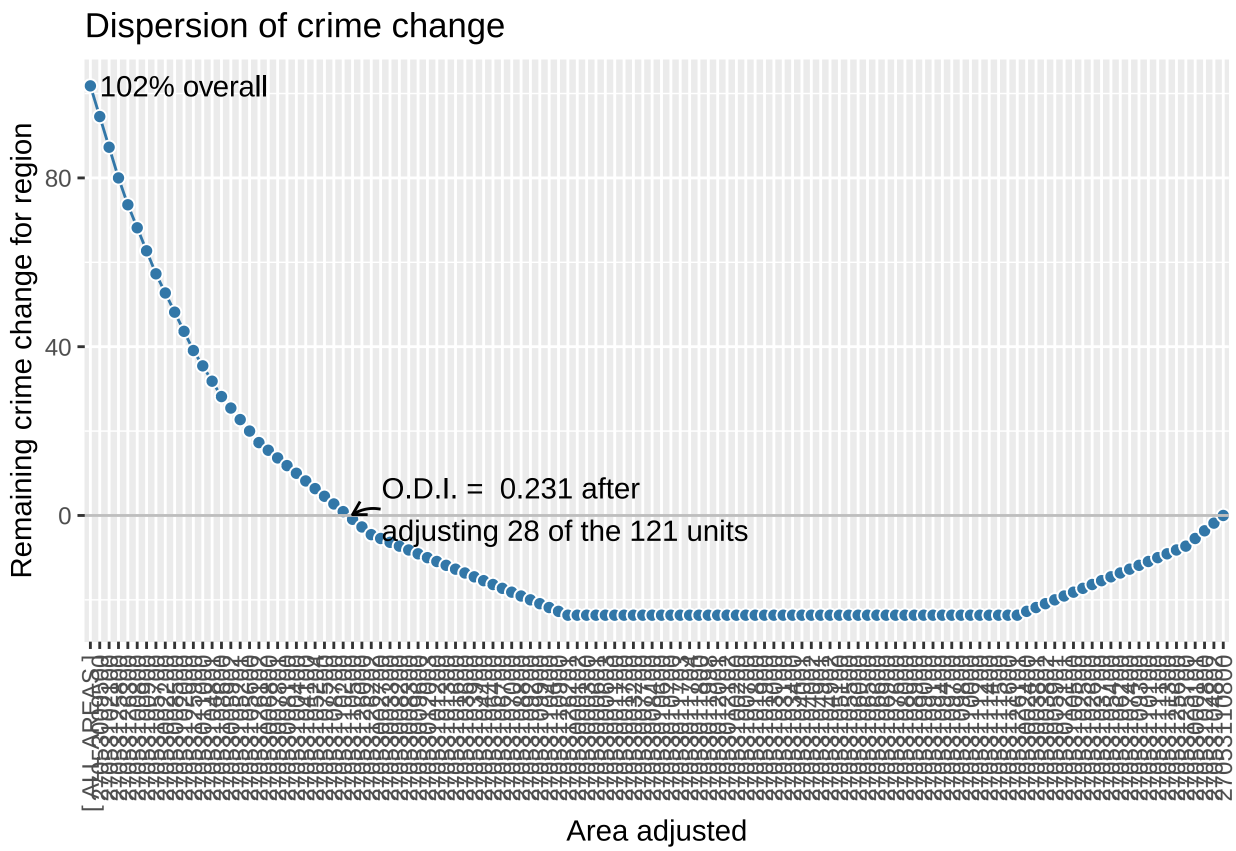
Homicide

```
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]]
```

```
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]]
```




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

Spatial Correlation *Change* in Carjackings and Homicide

Carjacking

```
library(sfdep)
```

```
## Warning: package 'sfdep' was built under R version 4.2.2
```

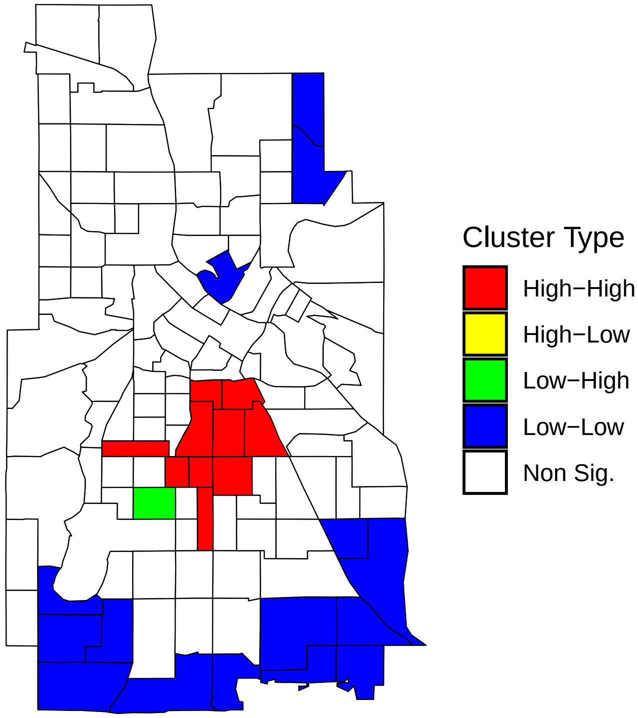
```
cj_delta <- prepost_cj %>%
  mutate(delta = car_jack_rate_1-car_jack_rate_0,
         GEOID = as.numeric(GEOID)) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  st_as_sf()

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

global_moran_test(
  cj_delta$delta,
```

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

```
##
##  Moran I test under randomisation
##
## data:  x
## weights: listw
##
## Moran I statistic standard deviate = 8.736, p-value < 2.2e-16
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##       0.453555803      -0.008333333       0.002795420
```

```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

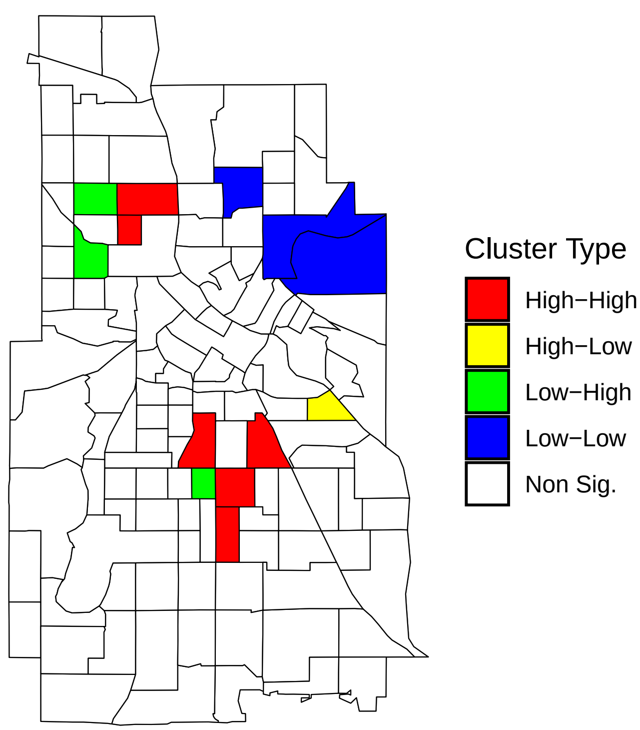
```
hom_delta <- prepost_hom %>%
  mutate(delta = homicide_1-homicide_0,
         GEOID = as.numeric(GEOID)) %>%
  left_join(mpls_tract, by = "GEOID") %>%
  st_sf()


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.")
```

Figure 8: LISA Plot for Homicide Change Pre/Post Police Murc



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_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)),
         t_post_floyd = ifelse(as.numeric(as.Date("2020-05-25")-begin_date)/7 >=0,
                               as.numeric(as.Date("2020-05-25")-begin_date)/7,
                               0),
        # 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")) %>%
  select(-med_hh_inc) %>%
  drop_na()



library(lme4)
```

```
## Warning: package 'lme4' was built under R version 4.2.2
```

```
library(lmerTest)
```

```
## Warning: package 'lmerTest' was built under R version 4.2.2
```

```
library(lavaan)
```

```
## Warning: package 'lavaan' was built under R version 4.2.2
```

```
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 943.629  7.286   7.286    0.198    0.198
## 14     unemp_rate ~~ female_hh_rate 704.567 -1.273  -1.273   -0.200   -0.200
## 15     unemp_rate ~~ no_hs_dip_rate   6.434  0.255   0.255    0.021    0.021
## 16       pov_rate ~~ female_hh_rate 443.948 -2.705  -2.705   -0.122   -0.122
## 17       pov_rate ~~ no_hs_dip_rate  58.088  1.936   1.936    0.046    0.046
## 18       pov_rate ~~     black_perc 110.356 -8.406  -8.406   -0.144   -0.144
## 19 female_hh_rate ~~ no_hs_dip_rate 105.301  0.598   0.598    0.082    0.082
## 20 female_hh_rate ~~     black_perc 719.519  5.183   5.183    0.514    0.514
```

```
## 21 no_hs_dip_rate ~~     black_perc 296.794 -7.281  -7.281   -0.382   -0.382
```

```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                         38357
##
## Model Test User Model:
##
##   Test statistic                              1610.419
##   Degrees of freedom                                 4
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             96458.724
##   Degrees of freedom                                10
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.983
##   Tucker-Lewis Index (TLI)                       0.958
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -606558.430
##   Loglikelihood unrestricted model (H1)    -605753.221
##
##   Akaike (AIC)                             1213138.861
##   Bayesian (BIC)                           1213232.962
##   Sample-size adjusted Bayesian (BIC)      1213198.004
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.102
##   90 Percent confidence interval - lower         0.098
##   90 Percent confidence interval - upper         0.107
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.029
##
## 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        3.428    0.023  148.576    0.000    3.428    0.726
##     pov_rate          8.295    0.067  123.883    0.000    8.295    0.590
##     female_hh_rate    2.155    0.013  164.248    0.000    2.155    0.740
##     no_hs_dip_rate    4.667    0.026  177.181    0.000    4.667    0.783
##     black_perc       17.544    0.074  236.523    0.000   17.544    0.960
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .unemp_rate ~~
##    .black_perc       -9.264    0.237  -39.009    0.000   -9.264   -0.555
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .unemp_rate       10.512    0.103  101.640    0.000   10.512    0.472
##    .pov_rate        128.929    0.964  133.780    0.000  128.929    0.652
##    .female_hh_rate    3.844    0.031  122.692    0.000    3.844    0.453
##    .no_hs_dip_rate   13.746    0.120  114.796    0.000   13.746    0.387
##    .black_perc       26.463    1.011   26.187    0.000   26.463    0.079
##     cd                1.000                               1.000    1.000
```

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


re <- lmer(car_jack_rate~t+post_floyd+t_post_floyd+
             conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+t_post_floyd: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 + t_post_floyd + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     t_post_floyd:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
## REML criterion at convergence: -75715.2
##
## Scaled residuals:
##    Min      1Q Median     3Q    Max
## -1.088 -0.236 -0.120  0.009 33.651
##
```

```
## Random effects:
##  Groups   Name        Variance  Std.Dev.
##  GEOID    (Intercept) 0.0001324 0.01151
##  Residual             0.0080504 0.08972
## Number of obs: 38357, groups:  GEOID, 121
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            5.038e-02  1.471e-02  1.154e+02   3.424 0.000855 ***
## t                      1.275e-07  1.077e-07  1.140e+02   1.184 0.238891
## post_floyd             2.200e-02  1.405e-03  3.823e+04  15.659  < 2e-16 ***
## t_post_floyd          -1.502e-05  1.192e-05  3.824e+04  -1.260 0.207564
## conc_dis               6.276e-04  2.114e-03  2.303e+02   0.297 0.766784
## age_19_29_perc        -4.565e-04  1.509e-04  1.140e+02  -3.024 0.003079 **
## age_30_49_perc        -3.651e-04  2.427e-04  1.140e+02  -1.504 0.135255
## age_50_69_perc        -1.036e-03  2.796e-04  1.140e+02  -3.705 0.000327 ***
## age_70_plus_perc      -5.255e-04  3.365e-04  1.140e+02  -1.561 0.121181
## post_floyd:conc_dis    1.100e-02  1.430e-03  3.823e+04   7.694 1.46e-14 ***
## t_post_floyd:conc_dis  2.172e-06  1.213e-05  3.823e+04   0.179 0.857935
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl t_pst_ cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.028
## post_floyd  -0.072 -0.005
## t_post_flyd -0.072  0.009  0.753
## conc_dis    -0.621  0.048  0.000  0.000
## ag_19_29_pr -0.932 -0.056  0.000 -0.001  0.592
## ag_30_49_pr -0.876 -0.098  0.001 -0.001  0.505  0.768
## ag_50_69_pr -0.739 -0.121  0.001 -0.001  0.520  0.725  0.442
## ag_70_pls_p -0.298 -0.032  0.000  0.000  0.161  0.280  0.278 -0.122
## pst_flyd:c_  0.000  0.000  0.000  0.000 -0.510  0.000  0.000  0.000  0.000
## t_pst_fly:_  0.000  0.000  0.000  0.000 -0.509  0.000  0.000  0.000  0.000
##             pst_:_
## t
## post_floyd
## t_post_flyd
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
## pst_flyd:c_
## t_pst_fly:_  0.753
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```
re_logit_cd <- glmer(anyjack ~ t+post_floyd+t_post_floyd+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+t_post_floyd: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| = 3.22747 (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 + t_post_floyd + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     t_post_floyd:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
##      AIC      BIC   logLik deviance df.resid
##  10400.9  10503.5  -5188.4  10376.9    38345
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.6628 -0.2102 -0.1348 -0.0736 24.3593
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  GEOID  (Intercept) 0.437    0.661
## Number of obs: 38357, groups:  GEOID, 121
##
## Fixed effects:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -3.288e+00  9.141e-01  -3.597 0.000322 ***
## t                      1.220e-05  7.948e-06   1.535 0.124896
## post_floyd             1.429e+00  1.294e-01  11.039  < 2e-16 ***
## t_post_floyd          -4.981e-03  1.371e-03  -3.633 0.000280 ***
## conc_dis               4.772e-01  1.444e-01   3.305 0.000950 ***
## age_19_29_perc        -8.910e-03  9.266e-03  -0.962 0.336285
## age_30_49_perc         6.753e-03  1.487e-02   0.454 0.649635
## age_50_69_perc        -6.220e-02  1.736e-02  -3.582 0.000340 ***
## age_70_plus_perc      -1.676e-02  2.048e-02  -0.818 0.413167
## post_floyd:conc_dis   -1.893e-01  1.025e-01  -1.846 0.064850 .
## t_post_floyd:conc_dis  1.494e-03  1.006e-03   1.484 0.137677
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl t_pst_ cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.098
## post_floyd  -0.133  0.008
## t_post_flyd -0.115 -0.001  0.805
## conc_dis    -0.625  0.104  0.325  0.278
## ag_19_29_pr -0.926 -0.006 -0.001  0.002  0.554
## ag_30_49_pr -0.864 -0.087  0.000  0.002  0.470  0.766
## ag_50_69_pr -0.728 -0.090 -0.003  0.001  0.465  0.722  0.442
```

```
## ag_70_pls_p -0.271 -0.018 -0.003  0.004  0.136  0.259  0.260 -0.145
## pst_flyd:c_  0.067 -0.010 -0.480 -0.390 -0.647 -0.001 -0.001  0.000  0.006
## t_pst_fly:_  0.062  0.011 -0.422 -0.533 -0.569 -0.003 -0.004 -0.002 -0.007
##             pst_:_
## t
## post_floyd
## t_post_flyd
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
## pst_flyd:c_
## t_pst_fly:_  0.800
## 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| = 3.22747 (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

homicide <- homicide %>% st_drop_geometry()

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+t_post_floyd+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+t_post_floyd: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 + t_post_floyd + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     t_post_floyd:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
## REML criterion at convergence: -133257.1
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -0.949 -0.103 -0.033 -0.005 45.524
##
## Random effects:
##  Groups   Name        Variance  Std.Dev.
##  GEOID    (Intercept) 1.616e-05 0.00402
##  Residual             1.798e-03 0.04240
## Number of obs: 38357, groups:  GEOID, 121
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            1.048e-02  5.484e-03  1.162e+02   1.911 0.058438 .
## t                      1.479e-08  4.006e-08  1.140e+02   0.369 0.712577
## post_floyd             2.403e-03  6.640e-04  3.823e+04   3.619 0.000296 ***
## t_post_floyd          -1.187e-05  5.633e-06  3.824e+04  -2.107 0.035096 *
## conc_dis               2.885e-03  8.548e-04  3.214e+02   3.375 0.000829 ***
## age_19_29_perc        -6.724e-05  5.616e-05  1.140e+02  -1.197 0.233666
## age_30_49_perc        -1.551e-04  9.029e-05  1.140e+02  -1.718 0.088588 .
## age_50_69_perc         1.605e-05  1.040e-04  1.140e+02   0.154 0.877668
## age_70_plus_perc      -2.741e-04  1.252e-04  1.140e+02  -2.189 0.030614 *
## post_floyd:conc_dis    2.393e-03  6.759e-04  3.823e+04   3.541 0.000399 ***
## t_post_floyd:conc_dis -1.408e-05  5.734e-06  3.823e+04  -2.455 0.014109 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl t_pst_ cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.028
## post_floyd  -0.091 -0.004
## t_post_flyd -0.091  0.007  0.753
## conc_dis    -0.570  0.045  0.000  0.000
## ag_19_29_pr -0.930 -0.056  0.000  0.000  0.545
## ag_30_49_pr -0.874 -0.098  0.000 -0.001  0.464  0.768
## ag_50_69_pr -0.738 -0.121  0.000 -0.001  0.478  0.725  0.442
## ag_70_pls_p -0.298 -0.032  0.000  0.000  0.148  0.280  0.278 -0.122
## pst_flyd:c_  0.000  0.000  0.000  0.000 -0.596  0.000  0.000  0.000  0.000
## t_pst_fly:_  0.000  0.000  0.000  0.000 -0.595  0.000  0.000  0.000  0.000
##             pst_:_
## t
## post_floyd
## t_post_flyd
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
```

```
## pst_flyd:c_
## t_pst_fly:_  0.753
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```
re_logit_cd_homicide <- glmer(anyhom ~ t+post_floyd+t_post_floyd+conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+t_post_floyd: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 + t_post_floyd + conc_dis + age_19_29_perc +
##     age_30_49_perc + age_50_69_perc + age_70_plus_perc + post_floyd:conc_dis +
##     t_post_floyd:conc_dis + (1 | GEOID)
##    Data: cj_exp_prepost
##
##      AIC      BIC   logLik deviance df.resid
##  10400.9  10503.5  -5188.4  10376.9    38345
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.6628 -0.2102 -0.1348 -0.0736 24.3593
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  GEOID  (Intercept) 0.437    0.661
## Number of obs: 38357, groups:  GEOID, 121
##
## Fixed effects:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -3.288e+00  9.141e-01  -3.597 0.000322 ***
## t                      1.220e-05  7.948e-06   1.535 0.124896
## post_floyd             1.429e+00  1.294e-01  11.039  < 2e-16 ***
## t_post_floyd          -4.981e-03  1.371e-03  -3.633 0.000280 ***
## conc_dis               4.772e-01  1.444e-01   3.305 0.000950 ***
## age_19_29_perc        -8.910e-03  9.266e-03  -0.962 0.336285
## age_30_49_perc         6.753e-03  1.487e-02   0.454 0.649635
## age_50_69_perc        -6.220e-02  1.736e-02  -3.582 0.000340 ***
## age_70_plus_perc      -1.676e-02  2.048e-02  -0.818 0.413167
## post_floyd:conc_dis   -1.893e-01  1.025e-01  -1.846 0.064850 .
## t_post_floyd:conc_dis  1.494e-03  1.006e-03   1.484 0.137677
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) t      pst_fl t_pst_ cnc_ds a_19_2 a_30_4 a_50_6 a_70__
## t           -0.098
## post_floyd  -0.133  0.008
## t_post_flyd -0.115 -0.001  0.805
## conc_dis    -0.625  0.104  0.325  0.278
## ag_19_29_pr -0.926 -0.006 -0.001  0.002  0.554
## ag_30_49_pr -0.864 -0.087  0.000  0.002  0.470  0.766
## ag_50_69_pr -0.728 -0.090 -0.003  0.001  0.465  0.722  0.442
## ag_70_pls_p -0.271 -0.018 -0.003  0.004  0.136  0.259  0.260 -0.145
## pst_flyd:c_  0.067 -0.010 -0.480 -0.390 -0.647 -0.001 -0.001  0.000  0.006
## t_pst_fly:_  0.062  0.011 -0.422 -0.533 -0.569 -0.003 -0.004 -0.002 -0.007
##             pst_:_
## t
## post_floyd
## t_post_flyd
## conc_dis
## ag_19_29_pr
## ag_30_49_pr
## ag_50_69_pr
## ag_70_pls_p
## pst_flyd:c_
## t_pst_fly:_  0.800
## 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| = 3.22747 (tol = 0.002, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
# random effects poisson - carjacking

rep <- glmer(car_jack~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 = poisson(link = "log"))
```

```
## 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| = 2.96766 (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?
```

```
#renb <- glmer.nb(car_jack~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+
```

```r
#           (1|GEOID),
 #      data = cj_exp_prepost)
```

```r
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", "T Post-Killing",
                               "Conc. Dis.", "Age 19-29", "Age 30-49",
                               "Age 50-69", "Age 70+",
                               "Post-Killing X Conc. Dis.",
                               "T Post-Killing 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)
```

RE CJ Models

```r
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", "T Post-Killing",
                               "Conc. Dis.", "Age 19-29", "Age 30-49",
                               "Age 50-69", "Age 70+",
                               "Post-Killing X Conc. Dis.",
                               "T Post-Killing 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",
```

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

	Carjacking	
	Rate per 1,000 RE HLM	Any Carjacking RE Logit
	(1)	(2)
T	0.00000	0.00001
	(−0.00000|0.00000)	(−0.00000|0.00003)
Post-Killing	0.022	1.429
	(0.019|0.025)	(1.175|1.682)
T Post-Killing	−0.00002	−0.005
	(−0.00004|0.00001)	(−0.008|−0.002)
Conc. Dis.	0.001	0.477
	(−0.004|0.005)	(0.194|0.760)
Age 19-29	−0.0005	−0.009
	(−0.001|−0.0002)	(−0.027|0.009)
Age 30-49	−0.0004	0.007
	(−0.001|0.0001)	(−0.022|0.036)
Age 50-69	−0.001	−0.062
	(−0.002|−0.0005)	(−0.096|−0.028)
Age 70+	−0.001	−0.017
	(−0.001|0.0001)	(−0.057|0.023)
Post-Killing X Conc. Dis.	0.011	−0.189
	(0.008|0.014)	(−0.390|0.012)
T Post-Killing X Conc. Dis.	0.00000	0.001
	(−0.00002|0.00003)	(−0.0005|0.003)
Constant	0.050	−3.288
	(0.022|0.079)	(−5.080|−1.496)
SD(Tract)	0.008	0.65
SD(Residual)	0.067	
Observations	38,357	38,357
Log Likelihood	37,857.610	−5,188.426
Note:	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 RE HLM	Any Homicide RE Logit
	(1)	(2)
T	0.000 (−0.00000|0.00000)	0.00002 (−0.00000|0.00004)
Post-Killing	0.002 (0.001|0.004)	0.572 (0.102|1.042)
T Post-Killing	−0.00001 (−0.00002|−0.00000)	−0.005 (−0.009|0.0002)
Conc. Dis.	0.003 (0.001|0.005)	0.989 (0.555|1.424)
Age 19-29	−0.0001 (−0.0002|0.00004)	0.016 (−0.011|0.044)
Age 30-49	−0.0002 (−0.0003|0.00002)	0.018 (−0.026|0.062)
Age 50-69	0.00002 (−0.0002|0.0002)	0.021 (−0.031|0.074)
Age 70+	−0.0003 (−0.001|−0.00003)	−0.042 (−0.106|0.022)
Post-Killing X Conc. Dis.	0.002 (0.001|0.004)	−0.047 (−0.376|0.283)
T Post-Killing X Conc. Dis.	−0.00001 (−0.00003|−0.00000)	−0.001 (−0.004|0.003)
Constant	0.010 (−0.0003|0.021)	−7.024 (−9.667|−4.382)
SD(Tract)	0.003	0.031
SD(Residual)	0.065	-
Observations	38,357	38,357
Log Likelihood	66,628.530	−1,666.711
Note:	95% Confidence Intervals in parentheses	

Spatial Panel Models

```
library(splm)
```

```
## Warning: package 'splm' was built under R version 4.2.2
```

```
nb <- st_contiguity(mpls_tract, queen=TRUE)
wt <-  st_weights(nb, style = "W")
w <- recreate_listw(nb, wt)


lag <- spml(car_jack_rate~t+post_floyd+t_post_floyd+
             conc_dis+
             age_19_29_perc+age_30_49_perc+age_50_69_perc+
             age_70_plus_perc+ post_floyd:conc_dis+t_post_floyd:conc_dis,
                     data = cj_exp_prepost,
             index = c("GEOID"),
            effect="individual",
             model="random",
             listw = w, lag=T, spatial.error="none")
summary(lag)
```

```
## ML panel with spatial lag, random effects
##
## Call:
## spreml(formula = formula, data = data, index = index, w = listw2mat(listw),
##     w2 = listw2mat(listw2), lag = lag, errors = errors, cl = cl)
##
## Residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.09997 -0.02119 -0.01058  0.00047 -0.00299  3.05336
##
## Error variance parameters:
##      Estimate Std. Error t-value  Pr(>|t|)
## phi 0.0153607  0.0023984  6.4046 1.508e-10 ***
##
## Spatial autoregressive coefficient:
##         Estimate Std. Error t-value  Pr(>|t|)
## lambda 0.0301777  0.0078266  3.8558 0.0001154 ***
##
## Coefficients:
##                         Estimate  Std. Error t-value  Pr(>|t|)
## (Intercept)           5.0382e-02  1.4300e-02  3.5233 0.0004261 ***
## t                     1.2738e-07  1.0462e-07  1.2175 0.2234120
## post_floyd            2.1357e-02  1.4046e-03 15.2055 < 2.2e-16 ***
## t_post_floyd         -1.4504e-05  1.1917e-05 -1.2171 0.2235707
## conc_dis              5.9293e-04  2.0714e-03  0.2862 0.7746911
## age_19_29_perc       -4.5822e-04  1.4667e-04 -3.1241 0.0017834 **
## age_30_49_perc       -3.6672e-04  2.3583e-04 -1.5550 0.1199410
## age_50_69_perc       -1.0413e-03  2.7165e-04 -3.8330 0.0001266 ***
## age_70_plus_perc     -5.2852e-04  3.2698e-04 -1.6164 0.1060129
## post_floyd:conc_dis   1.1031e-02  1.4298e-03  7.7147 1.213e-14 ***
## t_post_floyd:conc_dis 2.2532e-06  1.2131e-05  0.1857 0.8526452
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```