Incorporating time into studying crime and place (supplementary material)

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# 1 Identifying change over time

A common research question in the study of crime and place is whether the frequency of crime or some other phenomenon has changed as a result of a deliberate intervention or organic change in circumstances. It is common, for example, for researchers to study the impact of a place-based intervention by police, such as extra patrols or the installation of surveillance cameras. It is therefore important to have reliable methods for identifying changes in crime at places.

Many studies have used simple before-and-after research designs to understand changes in crime after an intervention, for example using a -test to compare pre- and post-intervention values of some outcome measure. For example, Earl, Cocksedge, Morgan, and Bolt (2017) used -tests to measure change in offending before and after participants were referred to a mental-health diversion scheme. Sousa and Madensen (2016) used the same approach to test whether the introduction of CCTV cameras was associated with a change in police calls for service.

[Figure 1 about here]

This simple before-and-after approach may be unwise for several reasons. Figure 1 shows the monthly frequency of a hypothetical crime over five years (using synthetic data), with an intervention introduced at the beginning of the fifth year. The figure shows there is a general upward trend in crime, a substantial drop in crime beginning the month *before* the intervention is introduced (possibly due to anticipatory benefits – see Smith, Clarke, & Pease, 2002), and an erosion of that drop over subsequent months so that by the end of the fifth year crime has returned to the level expected based on the pre-intervention trend.

A simple -test comparing the number of crimes in the year before and after the intervention occurred would suggest no difference between the frequency of crime before and after the intervention (, , , 95% CI [-0.55, 1.06]). However, this test ignores the crime trend (which also invalidates the assumption that the two samples in the -test are independent) and cannot distinguish between the apparent initial drop in crime and the subsequent increase back to pre-intervention levels. If the changes apparent in Figure 1 are due to the intervention, an approach based on -tests or similar methods could be misleading.

# 2 Example: testing changes in crime associated with community policing

In May 2015, the New York City Police Department (NYPD) introduced an initiative that rearranged officer assignments to create new roles – known as neighborhood coordination officers (NCOs) – who would focus on working with local communities to reduce crime (Bratton, 2015). The initiative began in four police precincts (33rd, 34th, 100th and 101st) in May 2015, before being expanded to other neighborhoods over time (NYC Office of the Mayor, 2016). We can use time-series methods to compare precincts to identify whether any changes in crime were associated with this initiative.

We will use data from the Open Crime Database, which contains crime data for large US cities over several years (Ashby, 2019). For the purpose of this example we will only analyze assaults, but a more-detailed analysis could also consider other crime types. We will do the analysis in R (the following code was run in R version 4.0.1), for which the crimedata package provides access to the Crime Open Database. We will use the tidyverse suite of packages (Wickham et al., 2019) for data processing, the sf package (Pebesma, 2018) for spatial operations and the tsibble package (Wang, Cook, & Hyndman, 2020) for handling time-series data. For an introduction to the pipe operator %>% see Bache (2014).

First we load the necessary packages:

# load packages  
library("crimedata") # major city crime data  
library("lubridate") # date handling  
library("sf") # spatial processing  
library("tsibble") # time-series processing  
library("tidyverse") # data processing

and data:

# load data from the Crime Open Database  
years\_to\_analyze <- 2010:2016  
# this next line may take a few minutes to run  
ny\_data <- get\_crime\_data(  
 years = years\_to\_analyze,   
 cities = "New York",   
 type = "core",   
 quiet = TRUE,   
 output = "sf"  
)

# download NYPD precinct boundaries  
precincts <- str\_glue(  
 "https://data.cityofnewyork.us/api/geospatial/78dh-3ptz?",   
 "method=export&format=GeoJSON"  
) %>%   
 read\_sf() %>%   
 st\_transform(2263)

Second, we identify which precinct each crime occurred in and group precincts into those included in the pilot phase and those that only received NCOs in October 2016. For this example, this comparison group has been chosen manually.

ny\_violence\_precincts <- ny\_data %>%   
 # filter out all crimes except assaults  
 filter(offense\_type %in% c("murder and nonnegligent manslaughter",   
 "aggravated assault")) %>%   
 # convert coordinates to local coordinate system  
 st\_transform(2263) %>%   
 # join the information in the precincts dataset (in particular,   
 # precinct number) to the crime data based on crime location  
 st\_join(precincts) %>%   
 mutate(group = case\_when(  
 precinct %in% c("33", "34", "100", "101") ~ "initiative",  
 precinct %in% c("26", "30", "60", "61") ~ "comparison",  
 TRUE ~ NA\_character\_  
 ))

We can now count the number of crimes occurring each week in the group of precincts that piloted the initiative and the comparison precincts.

violence\_counts <- ny\_violence\_precincts %>%   
 # remove the spatial data, since we no longer need it and it   
 # slows processing  
 st\_set\_geometry(NULL) %>%   
 # extract week of the year from offense date  
 mutate(week = yearweek(date\_single)) %>%   
 # filter out crimes that occurred before the first full week of  
 # the first year, as well as crimes in precincts that are not  
 # in either the initiative or comparison groups  
 filter(year(week) %in% years\_to\_analyze, !is.na(group)) %>%   
 # count number of offenses in each precinct group each week  
 count(group, week) %>%   
 # if no serious assaults occurred in a week in a precinct  
 # group, that week will be missing from the data, so we convert  
 # the counts to a time-series object that can detect missing  
 # rows and insert zero counts  
 as\_tsibble(key = group, index = week) %>%   
 fill\_gaps(n = 0) %>%   
 # then convert the data back to a normal data frame  
 as\_tibble() %>%   
 # finally, calculate whether each week occurred before or after  
 # the start date of the community policing initiative  
 mutate(initiative = week >= yearweek(ymd("2015-05-18")))

To compare serious violence in the precincts that piloted the initiative to the comparison precincts, we will use the difference-in-differences (DiD) approach (Angrist & Pischke, 2009) to compare the difference between the initiative and comparison precincts before the initiative to the difference after the initiative began. Using a comparison group allows us to deal with the issue of trends in time-series data, as long as the long-term trend is similar in both the intervention and comparison groups.

The DiD method requires that the trend in comparison precincts prior to the start of the initiative matches the trend in the initiative precincts – divergent trends can produce misleading results. We can compare the trends by plotting them on a chart (Figure 2), which shows the pre-initiative trend is very similar across the initiative and comparison precincts.

violence\_counts %>%   
 ggplot(aes(as\_date(week), n)) +   
 geom\_vline(aes(xintercept = ymd("2015-05-18")), color = "grey50") +  
 geom\_point(size = 0.75, color = "grey50", alpha = 0.5) +   
 geom\_smooth(  
 method = "lm", formula = "y ~ x", colour = "grey20",  
 data = filter(violence\_counts,   
 as\_date(week) < ymd("2015-05-18"))  
 ) +  
 geom\_smooth(  
 method = "lm", formula = "y ~ x", colour = "grey20",  
 data = filter(violence\_counts,   
 as\_date(week) >= ymd("2015-05-18"))  
 ) +  
 annotate("text", x = ymd("2015-04-01"), y = 32, hjust = 1,   
 size = 3.2, lineheight = 0.9,  
 label = "beginning of the\nNCO initiative") +  
 scale\_y\_continuous(limits = c(0, NA)) +  
 facet\_grid(  
 cols = vars(group),   
 labeller = as\_labeller(function (x) paste(x, "precincts"))  
 ) +   
 labs(x = NULL, y = NULL) +  
 theme\_minimal() +  
 theme(  
 panel.grid.major.x = element\_blank(),  
 panel.grid.minor.x = element\_blank(),  
 legend.position = "none"  
 )

[Figure 2 about here]

There are several different statistical models that we can use to implement the DiD approach. We could, for example, use generalized least squares (GLS) regression with correlated errors (Faraway, 2014). Since the weekly counts of crime are approximately normally distributed, the simplest approach is to run a linear regression and then adjust the standard errors so that we can draw inferences from the results even though the serial autocorrelation in the data violates one of the model assumptions.

The DiD approach uses the interaction between two terms in a regression model to estimate the means of four groups of weekly counts. For this example, we will not include any other terms in the model. If we suspected there was a difference in effect over time, or seasonal variation in crime, we could include additional variables to account for those patterns.

vio\_model <- lm(n ~ group \* initiative, data = violence\_counts)  
  
broom::tidy(vio\_model) %>%   
 mutate\_at(vars(estimate, std.error, statistic), scales::number) %>%   
 mutate(p.value = scales::pvalue(p.value)) %>%   
 knitr::kable(booktabs = TRUE, align = "lrrrr")

[Table 1 about here]

We can interpret the co-efficients (Table 1) as follows:

* the model intercept is the mean number of crimes per week in the comparison precincts before the initiative began,
* the groupinitiative co-efficient is the difference between the pre-initiative mean in the comparison and initiative precincts,
* the initiativeTRUE co-efficient is the difference between the pre- and post-initiative means in the comparison precincts, and
* the groupinitiative:initiativeTRUE interaction co-efficient is the difference between the post-intervention mean in the comparison and initiative precincts, independent of (i.e. minus) the pre-intervention difference between groups. It is the interpretation of this final co-efficient that is central to DiD analysis.

We can use the NeweyWest() function from the sandwich package (Zeileis, 2004) and the coeftest() function from the lmtest package to calculate standard errors and associated -values adjusted for autocorrelation (Zeileis & Hothorn, 2002).

lmtest::coeftest(vio\_model, vcov = sandwich::NeweyWest(vio\_model)) %>%   
 broom::tidy() %>%   
 mutate\_at(vars(estimate, std.error, statistic), scales::number) %>%   
 mutate(p.value = scales::pvalue(p.value)) %>%   
 knitr::kable(booktabs = TRUE, align = "lrrrr")

[Table 2 about here]

The results of this adjustment are shown in Table 2. They show that there were about 14 offenses of serious violence per week across the four comparison precincts before the intervention began (the model intercept), with the pre-intervention difference between the comparison and NCOs precincts (the groupinitiative term) not being significantly different. There was no significant difference in the frequency of serious assaults in the comparison precincts pre- and post-initiative (the initiativeTRUE term), but there was an increase of about three assaults per week associated with the post-intervention difference between precinct groups, independent of the pre-intervention difference. This is contrary to the objective of the initiative, which was to reduce crime.

The purpose of this example is not to evalute the NCO program, but to illustrate the process of identifying changes in crime over time. Obtaining a full answer to the question of whether the introduction of NCOs was associated with any change in the frequency of serious violence would need to consider whether there was any change in effect over time (e.g. if NCOs took time to become effective) and whether there was any variation between pilot precincts. A more-detailed analysis should also consider how to choose the best comparison precincts. Nevertheless, this simple example illustrates some of the issues involved in handling temporal data when studying crime and place.

# Availability of materials

The R code used to produce the charts in this document and the associated book chapter is available at https://osf.io/j5zth/

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*Figure* *1:*. Change in the frequency of crime before and after a hypothetical intervention

*Figure* *2:*. Linear trend in assaults in initiative and comparison precincts

Table 1: Difference-in-difference model results before adjusting standard errors

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| term | estimate | std.error | statistic | p.value |
| (Intercept) | 14.28 | 0.29 | 48.92 | <0.001 |
| groupinitiative | 0.22 | 0.41 | 0.53 | 0.598 |
| initiativeTRUE | 0.45 | 0.60 | 0.75 | 0.453 |
| groupinitiative:initiativeTRUE | 3.43 | 0.86 | 4.01 | <0.001 |

Table 2: Difference-in-difference model results after adjusting standard errors

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| term | estimate | std.error | statistic | p.value |
| (Intercept) | 14.28 | 0.48 | 30.05 | <0.001 |
| groupinitiative | 0.22 | 0.69 | 0.32 | 0.753 |
| initiativeTRUE | 0.45 | 0.94 | 0.48 | 0.630 |
| groupinitiative:initiativeTRUE | 3.43 | 1.32 | 2.60 | 0.010 |