Visualization and Causal Inference of the Mexican Drug War

Valeria Espinosa and Joseph Kelly
vespinos@fas.harvard.edu, kelly2@fas.harvard.edu
Statistics Department, Harvard University

Abstract

In Mexico, the presidency of Felipe Calderón (2006-2012) has been characterized for the war against organized crime, raising many questions regarding security and violence. **Do homicide rates increase significantly after a military intervention?**. As any good observational study, which mimics a randomized experiment, the *design* phase was completed without using the outcomes.

Estimand

Let $Y_i(1)$ and $Y_i(0)$ denote the homicide rate of region j one year after it received a military intervention, and what it would have been at that same point in time if it hadn't received the military intervention (Rubin Causal Model). Our estimand is the average causal effect of the military intervention for the regions that were intervened. That is

$$\tau = \bar{Y}(1) - \bar{Y}(0) = \frac{\sum_{i=1}^{I} Y_i(1) - Y_i(0)}{I}.$$

Let N_i denote the number of municipalities that correspond to region i, then

$$Y_i(1) = \sum_{i=1}^{N_j} w_{ij} Y_{ij}(1) \text{ and } Y_i(0) = \sum_{j=1}^{N_i} w_{ij} Y_{ij}(0),$$

$$\text{where } w_{ij} = \frac{\text{Pop}_{ij}}{\text{Pop}_i} \text{ and } \text{Pop}_i = \sum_{j}^{N_i} \text{Pop}_{ij}.$$

However, $Y_i(0)$ and $Y_{ij}(0)$ are missing $\forall i, j$.

Estimation

Propensity score matching was used to identify a set of 5 control municipalities that look like each treated ones, and ultimately estimate $Y_{ij}(0)$ and $Y_i(0)$. Let M_{ij} be the number of municipalities matched to the jth municipality in region i, and

$$\text{PopM}_{ij} = \sum_{k=1}^{M_{ij}} \text{PopM}_{ijk}$$

is the sum of their populations. Then,

$$\hat{Y}_{ij}(0) = \sum_{k=1}^{M_{ij}} v_{ijk} Y_{ijk}(0),$$

where $v_{ijk} = \frac{\text{PopM}_{ijk}}{\text{PopM}_{ij}}$. Therefore,

$$\hat{Y}_i(0) = \sum_{j=1}^{N_i} w_{ij} \hat{Y}_{ij}(0) = \sum_{j=1}^{N_i} w_{ij} \sum_{k=1}^{M_{ij}} v_{ijk} Y_{ijk}(0),$$

and

$$\hat{\tau} = \frac{\sum_j Y_j(1)}{J} - \frac{\sum_{j=1}^{J} \hat{Y}_j(0)}{J}.$$

Assumptions & Challenges

- **SUTVA** - stable unit treatment value assumption
  - **No hidden values of treatments** A broad definition of what "military intervention"- any mili means in this context helps us think of a two level treatment: receiving a military intervention (defined as ... see paper(that have resulted in deaths?)) or not receiving it.
  - **No interference between units** The main idea is to group neighboring regions that have received military interventions in such a way that distances make the "no interference" assumption more reasonable. For treated regions that are side to side were also assessed in terms of neighboring geographic situation such as lack of highways connecting them The last homicide rate that we have corresponds to 2010. That eliminated some of the interventions mentioned in the Nexos paper. Following this reasoning 2213 municipalities were included in the initial control pool. Our 13 treated regions are:

unit	Region	number of municipalities	Date of first intervention	Within Region Effect	SD Bin	SD Neyman	Effect- Gain Score within	SD Neyman G
1	**Tijuana**	5	2008	20.89	1.49	12.87	20.49	8.27
2	**Nogales**	5	2008	36.97	5.37	33.51	11.41	20.90
4	**Juárez**	15	2009	195.11	3.84	88.33	192.99	79.88
5	**Pánuco**	14	2007	-0.90	0.92	0.39	0.37	0.24
6	**Reynosa**	24	2008	0.87	0.87	1.23	-3.49	1.48
8	**Guadalupe**	20	2009	-5.06	0.59	0.89	-4.27	0.58
9	**Villa de Cos, Fresnillo**	18	2008	-1.35	1.24	0.44	-2.87	0.34
10	**Teúl de González Ortega,**	10	2009	13.83	5.52	9.21	7.32	4.99
11	**Rincón de Romos**	8	2008	-4.80	2.55	1.07	-4.10	1.05
12	**Sinaloa, Badiraguato, Pueblo Nuevo**	27	2007	4.33	1.19	1.15	-15.84	0.74
15	**Celaya**	9	2009	2.84	1.42	1.82	6.74	1.37
16	**Apatzingán**	10	2007	17.50	3.23	1.81	-52.81	5.97
18	**Acapulco**	35	2008	12.45	1.47	1.86	1.19	0.77
	Average	205	-	19.86	0.78	0.89	14.61	0.79

update this table to have the number of municipalities that received the intervention AND the main names. Put the image of the intervention map next to it

- **Unconfoundedness**: Unfortunately we didn't get experts to guide most of our decisions. However, we did get to interact with a couple of them and made our covariate choices based on the information received and our understanding of the relevant information. Our covariates include: location, political party before Calderón, income 2006, education and medical information at 2005, percentage of indigenous language speakers, 2006 homicide rate at the municipality level, and GDP, Homicide Rate and Population at the state level.
- **Missing Data:** there were few treated units that had one covariate (Doctors per medical unit) missing, we exactly matched on that and Political Party in power before Calderón.

Block Colours

For the standard blocks there are two colours; one for the title and one for the block body:

```
\setbeamercolor{block title}
{fg=red,bg=white}
\setbeamercolor{block body}
{fg=black,bg=white}
```

The *fg* colour sets the text colour and *bg* sets the background colour. For the normal blocks it makes no sense to use a background colour other than white. You *can* change it, but it will look weird!

Others

The "alert" block environment looks like this. It also has justified text, but it has a border and a light background to make it stand out. You can create one like so:

```
\begin{alertblock}{Title}
.......
\end{alertblock}
```

Alert Block Colours

You can similarly modify the colours for alert blocks (but try not to overdo it):

```
\setbeamercolor{block title}
{fg=black,bg=norange}
\setbeamercolor{block body}
{fg=black,bg=white}
```

Key References & Data Source

[1] Abadie Synthetic Matching
[2] Imbens G. & Rubin D.R., (2012)
[3] Rubin D.R. ,*Matched Sampling for Causal Effects*,
[4] Diego Valle visualization
[5] CIDAC