(Strategic) Models of Crime

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Motivation

- Between january 2012 and september de 2015, **all homicides and** 25 % **of all crimes reported in Bogotá occured in** 2 % of street segments.
- During the same period these segments received only 10 % **of the attention of police resources** (Blattman et.al 2017).
- We would like to predict. However, there is a strategic problem that cast doubt on the ability ot anticipate and reduce crime.

Introduction

- A Location Discrete Choice Model of Crime: Police Elasticity and Optimal Deployment. [1]
- Prediction models ignore **strategic reaction**.
- We use a unique experimental data to identify the causal impact of police patrolling on crime.
- Use of a **structural model of crime location choice**.
- Estimate **own-and cross-elasticities of crime to patrolling time**.
- **Evaluate alternative patrolling strategies**.

[1] Newball-Ramírez, D., Riascos, A., Hoyos, A. and M. Dulce. Submitted Plos One

Related Work

- Comprehensive study for the US: David Weisburd and Malay K. Majmundar. 2018. Proactive Policing: Effects on Crime and Communities.
- Aaron, Ch., and J. McCrary. 2018. Are U.S. Cities Underpoliced? Theory and Evidence:
  1. Police elasticity (number of policemen) of violent crime between -0.289 to -0.361.
  2. Property crimes of -0.152 to -0.195.

Related Work

- Blattman, Ch., Green, D.,Ortega, D. and S. Tobón. 2021. Place-based interventions at scale: The direct and spillover effects of policing and city services on crime.
    1. Randomly assigned 756 (206) streets to an 8-month treatment of doubled police patrols (greater municipal services) and measure the direct effect.
    2. Measures spillovers (indirect effects) in streets in a radius of 250 meters: $52,095$ $(21,286)$.
    3. Confidence intervals suggest they can rule out total reductions in crime of more than 2 %.

Spatial Discrete Choice Model

- N potential criminal offenders with symmetric preferences, each of them deciding between $J+1$ locations in the city to commit a crime.
- The associated utility u_{ij}, of agent i, of selecting location j, is given by

$$u_{ij} = \alpha P_j + X_j\beta + \xi_j + \varepsilon_{ij} \tag{1}$$

where:

  - P_j police presence in location j.
  - X_j: K observed characteristics of the location.
  - ξ_j:unobserved characteristics of location j.
  - ε_{ij}: idiosyncratic error term.

Spatial Discrete Choice Model

- Assume $\varepsilon_{ij}, \varepsilon_{ij'}$ are i.i.d. extreme value type I distributed, location choice probabilities are:

$$s_{ij}(P_j, X_j, \xi_j; \alpha, \beta) = \frac{\exp(\alpha P_j + X_j\beta + \xi_j)}{1 + \sum_{k=1}^{J} \exp(\alpha P_k + X_k\beta + \xi_k)} \quad (2)$$

  where option $j = 0$ is assumed to be the **outside option**.

- By symmetry of preferences:

$$S_j(P_j, X_j, \xi_j; \alpha, \beta) = s_{ij}(P_j, X_j, \xi_j; \alpha, \beta)$$

Spatial Discrete Choice Model

- Own- and cross-elasticities of crime:

$$\frac{\partial S_j}{\partial P_\ell} = \begin{cases} \alpha S_j(1 - S_j) & \text{if } j = \ell \\ -\alpha S_j S_\ell & \text{if } j \neq \ell \end{cases} \tag{3}$$

and

$$E_{S_j, P_\ell} \equiv \frac{\partial S_j}{\partial P_\ell} \frac{P_\ell}{S_j} = \begin{cases} \alpha(1 - S_j) P_j & \text{if } j = \ell \\ -\alpha S_\ell P_\ell & \text{if } j \neq \ell \end{cases}. \tag{4}$$

Estimation

- To estimate the structural parameters $\theta = (\alpha, \beta)$ from equation (1) we note that:

$$\delta_j = \mathtt{log}(S_j) - \mathtt{log}(S_0) = \alpha P_j + X_j \beta + \xi_j, \tag{5}$$

Estimation: Endogeneity

Figura 1: OLS estimation: Biased estimates

Estimation: TSLS

- Starting in January 2016 and during 8 months, 756 out of 1,919 street segments labeled as crime hot spots (out of the 136,984 street segments) received a doubled patrolling time
- We used this randomized treatment to **instrument** the police presence P_j and identify α.

Results: Estimation (Double Selection)

Table 2: TSLS α estimates for the discrete spatial location choice model

	Violent crimes				Property crimes				Total crimes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	-0.004*	-0.003*	-0.005*	-0.006**	-0.004**	-0.005***	-0.009**	-0.008*	-0.005**	-0.005***	-0.008**	-0.008*
	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)
Observations	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Past police presence	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Locality FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
R-squared	-0.023	0.309	0.310	0.380	0.000	0.339	0.340	0.414	-0.035	0.187	0.190	0.281

Notes: *** p<0.01, ** p<0.05, * p<0.1. Cluster robust standard errors at the level of locality in parentheses.

Figura 2: α TSLS estimation after double selection.

Results:Estimation Direct Elasticities

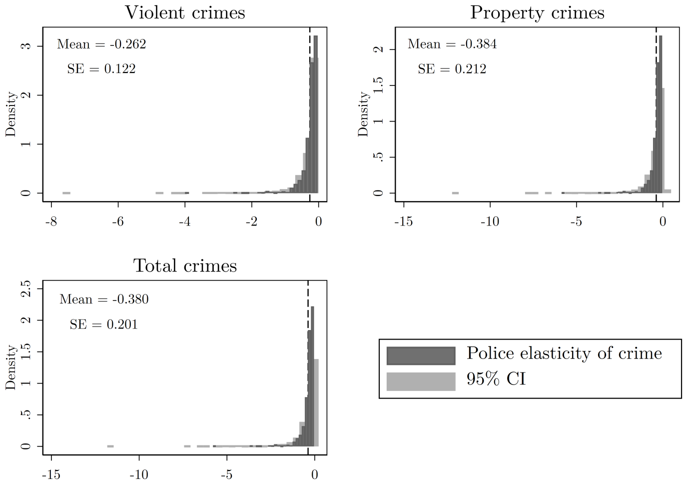

Figura 3: Impact of police presence on crime in the same location.

Results:Estimation Cross Elasticities

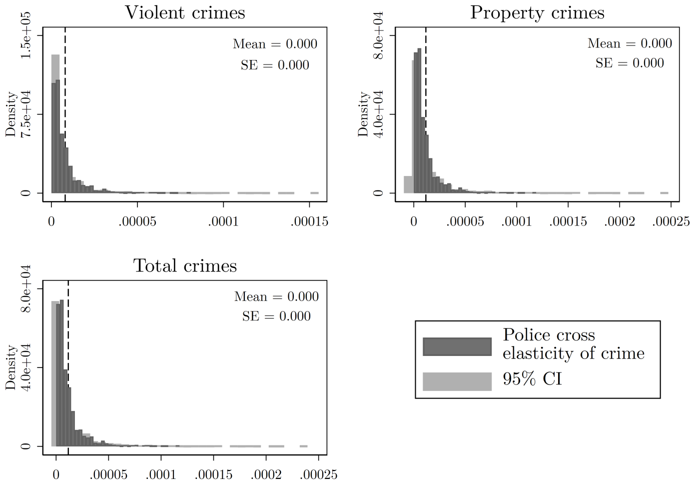

Figura 4: Impact of police presence on crime in different locations.

Optimal Policy

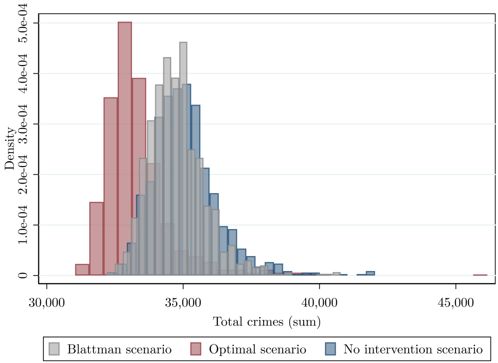

Figura 5: Optimal Policy vs Blattman and No Intervention: Bootsraped estimation

Conclusions

- Switching to the optimal time allocation policy, average reduction of
  - $-7\,\%$ violent crimes per quadrant.
  - $-8.5\,\%$ in property crimes.
  - $-5.2\,\%$ in total crimes.
- That is a reduction of 862 violent crimes, $1,919$ property crimes and $1,763$ in one year.

Introduction

- Police Presence, Rapid Response Rates, and Crime Prevention.[2]
- They use data of exact police patrol cars of Dallas Police Department (2009).
- To address endogeneity, they exploit the police response to calls outside of their allocated coverage beat.
- Main result: 10 % increase in police presence at a location reduces crime in 7 %

[2] Sarit Weisburd; Police Presence, Rapid Response Rates, and Crime Prevention. The Review of Economics and Statistics 2021; 103 (2): 280–293. doi: https://doi.org/10.1162/rest$_{a}$0889

Introduction

- The main idea is that outside calls from a specific location (beat: geographical patrol area of 1.7 square miles) are almost random. Hence, changes in police presence due to patrol cars that move off their assigned and planed location into another location are almost random.
- However, crimes may correlate across locations, hence only some calls are taken into account: mental health, child abandnment, fire, animal attacks, dead people, suicides, abandoned properties, fireworks and drug houses.
- Reports of crime are not included in these outside calls.

Empirical Strategy

- Divide Dallas in 232 geographical areas (beats).
- Estimate:

$$C_{bh} = x_{bh}\beta_0 + \beta_1 P_{bh} + \gamma_t + \eta_b + \epsilon_{bh} \tag{6}$$

where C_{bh} is the count of 911 call reporting incidents of crime, burglaries, thefts and public disturbances at beat b and hour h, x_{bh} are covariates and P_{bh} is the time police officers spend at beat b and hour h.

Empirical Strategy

- P_{bh} is likely not exogenous. Hence they propose a first stage:
- Estimate:

$$P_{bh} = x_{bh}\alpha_0 + \alpha_1 OC_{bh} + \theta_t + \rho_b + \delta_{bh} \quad (7)$$

If the intuition is correct we expect α_1 to be negative.

Endogeneity

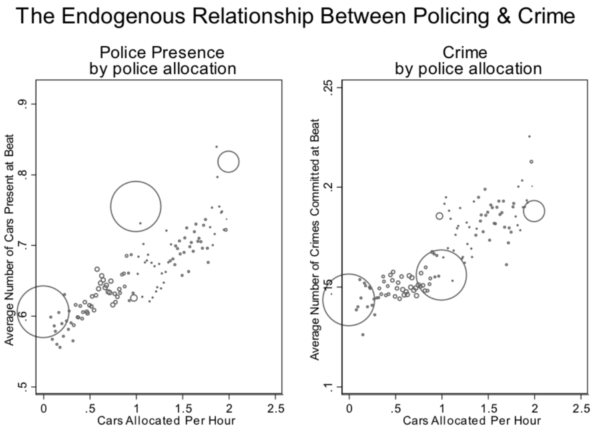

Figure 1: The data was collapsed at each vehicle allocation point. Generally either 0,1, or 2 cars are allocated to patrol a given beat at a given hour. However, if a car did not begin or end patrol on the hour this results in a fraction of car allocation. The size of

Instrumental Variable

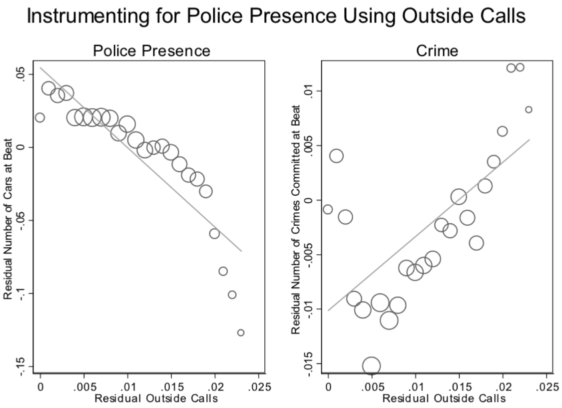

Figure 3: Residuals were calculated for police presence, crime, and outside calls by regressing each variable on weather, time of day, and date characteristics. I drop residuals that are not found across all beats or appear in less than 10 percent of the sample. The

First Stage Regression

Table 2: Outside Calls as Predictors of Police Presence

	Instrument=OC Ratio[1]		Instrument=Outside Calls[2]	
	OCR	Interactions	OC	Interactions
Instrument	-0.055***		-0.078***	
	(0.003)		(0.026)	
Instrument x South Central		-0.080***		-0.687***
		(0.008)		(0.051)
Instrument x Southeast		-0.044***		-0.224***
		(0.009)		(0.050)
Instrument x Southwest		-0.044***		0.016
		(0.006)		(0.065)
Instrument x North Central		-0.070***		0.107
		(0.008)		(0.071)
Instrument x Northeast		-0.052***		-0.273***
		(0.006)		(0.053)
Instrument x Northwest		-0.055***		-0.032
		(0.006)		(0.069)
Instrument x Central		-0.052***		0.834***
		(0.009)		(0.110)
Beat Fixed Effects	Yes	Yes	Yes	Yes
Month & Day of Week FE	Yes	Yes	Yes	Yes
Weekend X Hour FE's	Yes	Yes	Yes	Yes
Observations	2,017,676	2,017,676	2,017,676	2,017,676

Notes: Each observation is a beat and hour in 2009. Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. Standard

Second Stage Regression

Table 3: The Effect of Police Presence on Crime

	OLS (1)	IV= Outside Calls Ratio[2] (2)	IV= Outside Calls[3] (3)
Police Vehicles[1]	0.012***	-0.185***	-0.181***
	(0.0004)	(0.032)	(0.054)
Temperature	0.002***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)
Precipitation	-0.001***	-0.001***	-0.001***
	(0.0003)	(0.0004)	(0.0004)
Twilight	0.007***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
Holiday	0.013***	-0.006	-0.006
	(0.004)	(0.006)	(0.007)
Dark	-0.00002	0.0004	0.0004
	(0.002)	(0.003)	(0.003)
Beat FE's	Yes	Yes	Yes
Month FE's	Yes	Yes	Yes
Day of Week FE's	Yes	Yes	Yes
Weekend X Hour FE's	Yes	Yes	Yes
1st Stage F Stat		321.73	40.81
Observations	2,017,676	2,017,676	2,017,676

Notes: Each observation is a beat and hour in 2009. The average crime rate is 0.15 (s.d. 0.4), average police presence is 0.605 (s.d. 1.078). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours.

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

Introduction

- We model the interaction between attacker and defenders as a Stackelberg game (security game).
- Defender moves first and the attacker observes its moves and acts strategically.
- The Defender internalizes this behavior.
- The model focus in spatio-temporal incidents.

Model

- Remember the Poisson distribution: $f(X = k) = \frac{\lambda^k \exp(-\lambda)}{k!}$, $\lambda = E[\lambda] = VaR(\lambda)$
- Consider a region divided in G cells. Let $g_i \in G$ be a cell.
- Consider a dataset D divided into T-time steps. Let x_i^t be the number of incidents at time t in region g_i.
- Assume that incidents in a given cell i at time t follow a Poisson random variable with mean $u_{it} = \theta^T w_{it}$.
- La función de verosimilitud de los incidentes es (asumiendo independencia):

Model: Verosimilitud

- La función de verosimilitud de los incidentes es (asumiendo independencia):

$$F(x;\theta,w) = \prod_{t=1}^{T} \prod_{g_i \in G} \frac{\mu_{it}^{x_i^t} \exp(-\mu_{it})}{x_i^t!}$$

Model: Attacker strategies

- Let N_i be the neighbours of cell g_i. The attacker is allowed to move to any of the neighboring cells to commit crime and evade detection.
- Let $s_j^i \in \{0, 1\}$, denotes the shift of the attacker to cell $g_j \in G$.
- Strategies can make only one shift.

Model: Attacker/Defender Problem

- The attacker problem is:

$$\min_{s \in S} F(x(s); \theta, w)$$

  where S is the set of all possible spatial shifts over all incidents and s is a feasible incident.

- The Defender problem is:

$$\max_{\theta} \min_{s \in S} F(x(s); \theta, w)$$

Crime Prediction

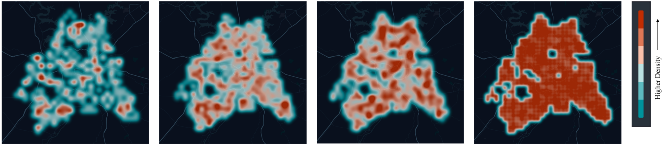

Figure 4: Predicted incident density for incidents plotted according to a varying attacker budget. Images from lef right are plotted with an attacker budget of 0, 1, 2 and 3 respectively.

Figura 10: Crime Prediction

Thanks

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