A Spatial Discrete Choice Model of Crime

Alvaro J. Riascos[1, 2] Douglas Newball-Ramírez[1, 2]
Mateo Dulce[3] Andrés Hoyos[1, 2]

[1] Universidad de los Andes

[2]Quantil

[3]Carnegie Mellon

16 de junio de 2022

What we do...

- The causal relationship between proactive policing (in the sense of more time of police presence) and the incidence of crime is not yet well established.
- We use a unique experimental data set to identify the causal impact of police patrolling on crime. We exploit an identification strategy based on a random utility model of crime location choice.
- We estimate own-and cross-elasticities of crime to patrolling time and we were able to evaluate alternative patrolling strategies.

Results

- Our estimates show that 1 % more time patrolling reduces crime an average of 0.19 %. Cross-price elasticities show little support to negative spillover effects of police patrolling.
- Allocating police time according to crime incidence and the elasticities of each quadrant, could potentially reduce violent crime by 4.13 % and property crime by 6 %.

Motivation

- Crime prediction is now ubiquitous in crime prevention and police resource planning.
- There is already a vast literature.
- Equilibrium interaction (endogeneity): The optimal allocation of police resources is guided by police deployment strategies (e.g., prediction models), which at the same time determine what crime incidents are reported or how crime is displaced from one sector to another.

Literature

- The evidence on the effects of proactive policing is mixed (see National Academies of Sciences y Medicine (2018) for a comprehensive study for the US).
- Braga y col. (2015) Identified 30 randomized experimental suggesting that policing disorder strategies are associated with an overall statistically significant modest crime reduction.
- Telep y col. (2014) Reviewed 19 publications covering 20 quasi-experimental studies. They found no significant overall evidence of displacement or a diffusion of benefits.
- Ratcliffe y col. (2011) reported the results of a randomized controlled trial of police effectiveness across 60 violent crime hot spots in Philadelphia. Their results suggested a significant reduction in the level of violent crime for the treated area after 12 weeks. Targeted areas outperformed the control sites by 23 %.

Literature

- Novak y col. (2016) examined the effectiveness of foot patrol in violent micro-places in Kansas City. Their results reveal statistically significant short-run reductions in violent crime in the micro-places receiving foot patrol treatment. They found no evidence of crime displacement to spatially contiguous areas.
- Fitzpatricka y col. (2020) conducted a controlled field experiment of police placed-based interventions on violent crime. They found statistically significant reductions in serious violent crime counts within treatment hot spots as compared to control hot spots, with an overall reduction of 25.3 % in violent crimes such as homicides, rape, robbery, and aggravated assault.

Literature

- Blattman y col. (2021), a placed-based police and city services intervention at scale for Bogotá D.C., Colombia. The authors randomly assigned 1,919 streets to an 8-month treatment of doubled police patrols, greater municipal services, both, or neither. They found that increasing state presence has modest direct impacts. Confidence intervals suggest they can rule out total reductions in crime of more than 2 %.

Literature

- In Bernasco y Nieubeerta (2005), the authors studied the selection of crime (burglary) locations in the city of The Hague, Netherlands. They used sociodemographic data of 290 burglars who committed 548 burglaries in the city during the period 1996-2001. They estimated a random utility model with burglars' and burglaries' characteristics by means of a conditional logit model. There is no causal identification of the effect of police patrolling on crime.

Contribution

1. We use a unique large data set of experimental data that allows for the identification of the causal effect of police patrolling on crime.
2. Our identification strategy is based on random utility selection of spatial locations for crime.
3. We used double selection techniques for a more agnostic data-driven model specification and robustness check of our results.
4. We computed the police own- and cross-elasticity of crime for each of the quadrants
5. Counterfactual strategies without increasing the total police time available: (a) uniformly across quadrants, (b) proportional to the incidence of crimes, (c) such that the more insecure and elastic quadrants receive either a 10 - 100 % increase, and (d) recursively increasing 1 % of patrol time for the most insecure and elastic quadrant.

Spatial Discrete Choice Model

- Consider N potential criminal offenders with symmetric preferences, each of them deciding between $J+1$ locations in the city to commit a crime.
- Each potential offender bases her location choice on her perceived utility of committing a crime in each of the $J+1$ locations.
- 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 is a measure of the police presence in location j, X_j is a vector of K observed characteristics of the location, ξ_j is the unobserved characteristics of location j, ε_{ij} is the idiosyncratic error term.

Spatial Discrete Choice Model

- Assuming $\varepsilon_{ij}, \varepsilon_{ij'}$ are i.i.d. extreme value type I distributed, location choice probabilities have a closed-form expression given by

$$s_{ij}(P_j, X_j, \xi_j; \alpha, \beta) = \frac{\exp(\delta_j)}{1 + \sum_{k=1}^{J} \exp(\delta_k)} \tag{2}$$

  where option $j = 0$ is assumed to be the *outside option* and $\delta_j = \alpha P_j + X_j \beta + \xi_j$.

- Due to the assumed symmetry of preferences it follows that the share of committed crimes at location j:

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

Spatial Discrete Choice Model

- Own- and cross-elasticities of crime with respect to police presence P_j (or any observed characteristic $x_{rj} \in X_j$) are given by

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

and thus, the police own- and cross-elasticities of crime are

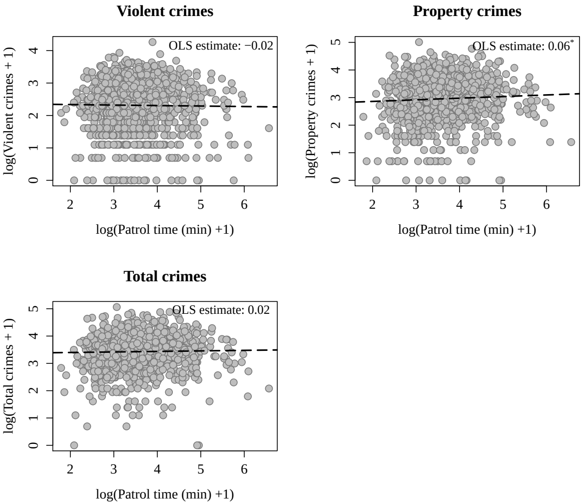
$$E_{S_j,P_\ell} \equiv \frac{\partial S_j}{\partial P_\ell}\frac{P_\ell}{S_j} = \begin{cases} \alpha(1 - S_j)P_j & \text{if } j = \ell \\ -\alpha S_\ell P_\ell & \text{if } j \neq \ell \end{cases}. \tag{4}$$

Estimation

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

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

Estimation: Endogeneity



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 of the city - received a doubled patrolling time (92-167 minutes of police patrol per day) Blattman y col. (2021).
- In March 2016, 201 of the 1,919 hot spots received more intensive street light repair and cleaning Blattman y col. (2021).
- We used the first type of treatment to instrument the police presence P_j and identify the structural parameters of interest. That is, we estimate equation (5) by TSLS.

Estimation: TSLS

- The necessary assumptions for the treatment assignment, Z, to be a valid instrument are:
  1. Independence.
  2. Exclusion restriction: Z only affects δ_j through P_j.
  3. Rank condition (relevance): *"police complied with their new orders for the full 8 months."*.
  4. Monotonicity (no defiers): police officers were monitored via GPS every 30 seconds and police officers plausibly double their efforts in a task only when they are ordered.

Estimation: Double Selection

- To select the variables that should be included in X_j we implemented the double selection methodology of Belloni y col. (2014).
- We first (separately) ran a regularized lasso over the following two equations:

$$\delta_j = \tilde{X}_j \gamma + \mu_j, \tag{6}$$

$$P_j = \tilde{X}_j \vartheta + \lambda_j, \tag{7}$$

where $\tilde{X}_j$ is a vector of variables that includes all the available and exogenous location features and all their second degree interaction terms, while μ_j and λ_j are the error terms.

Results: Estimation

Table 4: TSLS β estimates for double-selection selected covariates that predict δ_j

	Violent Crimes (1)	Property Crimes (2)	Total Crimes (3)
Avg. dist. to nearest shopping center	-	-0.001	-
	-	(0.001)	-
Avg. dist. to nearest shopping center× Prop. of paved segments	-	-0.0001	-
	-	(0.001)	-
N	1,018	1,018	1,018
Adj. R^2	0.307	0.396	0.216

Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity robust standard errors in parentheses (HC1). Double-selection selected variables that explain P_j excluded since there were 89 selected variables and their interpretation would be cumbersome. Avg.: Average. Prop.: Proportion. Dist.: distance

Results: Estimation

Table 5: Double-selection selected covariates that predict P_j

	Prop. of paved segments	Prop. of street segments zoned for industry/commerce	Prop. of street segments zoned for service sector	Prop. of high income street segments	Prop. of middle income street segments	Avg. dist. to nearest shopping center	Avg. dist. to nearest education center	Avg. dist. to nearest park/recreational center	Avg. dist. to nearest religious center	Avg. dist. to nearest health center	Avg. dist. to nearest additional services center center	Avg. length of street segments	Avg. built meters per meter of street segment
A. Linear selected variables			✓										
B. Quadratic selected variables													
Prop. of paved segments	✓	✓	✓			✓	✓	✓	✓	✓	✓		
Prop. of street segments zoned for industry/commerce	✓	✓	✓	✓		✓	✓	✓		✓	✓		✓
Prop. of street segments zoned for service sector	✓	✓	✓		✓			✓	✓	✓	✓		✓
Prop. of high income street segments	✓	✓			✓	✓	✓					✓	
Prop. of middle income street segments			✓		✓	✓		✓	✓	✓			✓
Avg. dist. to nearest shopping center	✓				✓	✓		✓					✓
Avg. dist. to nearest education center				✓						✓	✓	✓	✓
Avg. dist. to nearest park/recreational center	✓	✓	✓			✓							✓
Avg. dist. to nearest religious center	✓		✓		✓								✓
Avg. dist. to nearest health center		✓			✓		✓				✓		✓
Avg. dist. to nearest additional services center center	✓	✓	✓				✓			✓	✓		
Avg. length of street segments				✓			✓					✓	
Avg. built meters per meter of street segment		✓	✓		✓	✓	✓	✓	✓	✓			✓

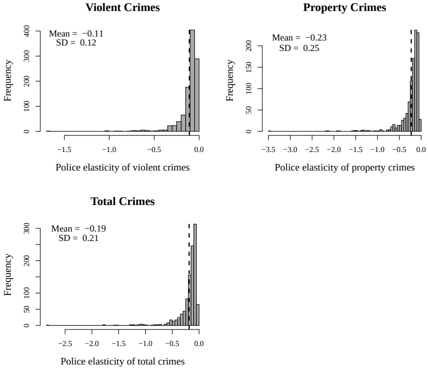
Notes: Panel A presents check marks (✓) for the linear double-selection selected variables. This is the variables in their base form. Panel B presents check marks (✓) for the quadratic double-selection selected variables. In this case, a check mark in row ℓ and column m indicates that the interaction between variables ℓ and m was selected. No coefficients are displayed to avoid cumbersome interpretations. Panel B is a symmetric matrix of check marks.

Results: Estimation

Table 2: α estimates from different econometric methodologies

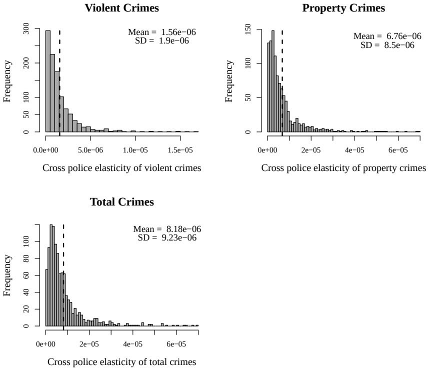
	Violent Crimes (1)	Property Crimes (2)	Total Crimes (3)
A. OLS			
α estimate	-0.001	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)
N	1,026	1,040	1,047
Adj. R^2	0.282	0.348	0.194
B. Double Selection			
α estimate	-0.001	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
N	1,018	1,018	1,018
Adj. R^2	0.316	0.404	0.225
C. TSLS			
α estimate	-0.002	-0.005***	-0.003**
	(0.001)	(0.002)	(0.001)
N	1,026	1,040	1,047
Adj. R^2	0.277	0.338	0.189
D. TSLS + Double Selection			
α estimate	-0.003	-0.004***	-0.004**
	(0.002)	(0.002)	(0.001)
N	1,018	1,018	1,018
Adj. R^2	0.307	0.396	0.216

Results:Estimation



(a) Police elasticity of crime

Results:Estimation



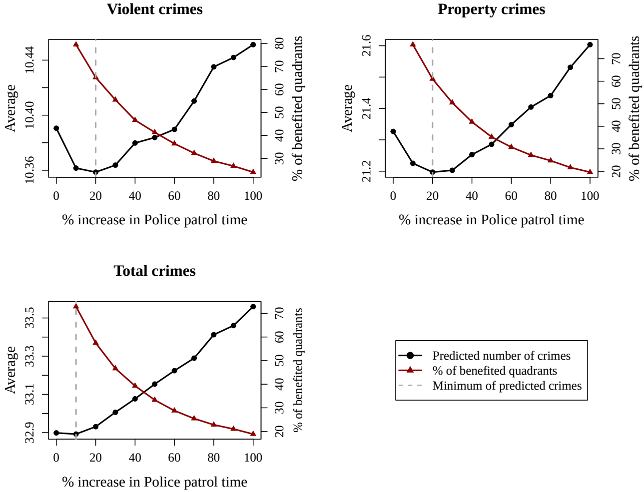
(b) Cross police elasticity of crime

Results

Table 6: Counterfactual analysis of different types of police patrol assignments

	Violent Crimes			Property Crimes			Total Crimes		
	Benefited Q. N	Benefited Q. %	Predicted # Mean (SD)	Benefited Q. N	Benefited Q. %	Predicted # Mean (SD)	Benefited Q. N	Benefited Q. %	Predicted # Mean (SD)
A. Base scenario									
Observed	-	-	12.31	-	-	24.61	-	-	36.92
	-	-	(8.51)	-	-	(17.89)	-	-	(21.18)
Predicted	-	-	10.39	-	-	21.33	-	-	32.90
	-	-	(4.12)	-	-	(9.90)	-	-	(9.44)
B. Counterfactual scenarios									
Uniform	544	53.43	10.68	544	53.43	22.64	544	53.43	34.37
			(4.12)			(11.12)			(10.22)
Proportional time	514	50.49	10.40	511	50.19	21.73	516	50.68	33.39
			(4.15)			(11.03)			(11.03)
Reassignment 3									
0% increase (Base case)	0	0.00	10.39	0	0.00	21.33	0	0.00	32.90
			(4.12)			(9.90)			(9.44)
10% increase	809	79.47	10.36	776	76.23	21.23	742	72.89	32.89
			(4.06)			(9.70)			(9.37)
20 % increase	664	65.23	10.36	621	61.00	21.20	585	57.47	32.93
			(4.06)			(9.63)			(9.47)
30 % increase	565	55.50	10.36	514	50.49	21.20	475	46.66	33.01
			(4.05)			(9.64)			(9.64)
40 % increase	475	46.66	10.38	427	41.94	21.25	400	39.29	33.08
			(4.09)			(9.71)			(9.81)
50% increase	421	41.36	10.38	359	35.27	21.29	339	33.30	33.15
			(4.09)			(9.75)			(9.99)
60 % increase	371	36.44	10.39	313	30.75	21.35	293	28.78	33.22
			(4.12)			(9.85)			(10.12)
70% increase	329	32.32	10.41	277	27.21	21.40	259	25.44	33.29
			(4.16)			(9.94)			(10.20)
80 % increase	294	28.88	10.44	252	24.75	21.44	232	22.79	33.41
			(4.21)			(10.01)			(10.51)
90 % increase	272	26.72	10.44	221	21.71	21.53	214	21.02	33.46
			(4.23)			(10.13)			(10.64)
100% increase	245	24.07	10.45	200	19.65	21.60	192	18.86	33.56
			(4.26)			(10.24)			(10.83)
Reassignment 4	513	50.39	9.96	538	52.84	20.04	636	62.47	32.00
			(2.80)			(5.97)			(5.43)

Results


Violent crimes
Average
% of benefited quadrants
% increase in Police patrol time
Property crimes
Average
% of benefited quadrants
% increase in Police patrol time
Total crimes
Average
% of benefited quadrants
% increase in Police patrol time
Predicted number of crimes
% of benefited quadrants
Minimum of predicted crimes

Conclusions

- Our estimates show that 1 % more time patrolling reduces crime an average of 0.19 %.
- Cross-price elasticities show little support to negative spillover effects of police patrolling.
- Allocating police time according to crime incidence and the elasticities of each quadrant, could potentially reduce violent crime by 4.13 % and property crime by 6 %.

Belloni, A., Chernozhukov, V. & Hansen, C. (2014). High-dimensional methods and inference on structural and treatment effects. *Journal of Economic Perspectives, 28*(2), 29-50.

Bernasco, W. & Nieubeerta, P. (2005). How do residential burglars select target areas. *British Journal Criminology, 44*(4), 296-315.

Blattman, C., Green, D. P., Ortega, D. & Tobón, S. (2021). Place-based interventions at scale: The direct and spillover effects of policing and city services on crime. *Journal of the European Economic Association, 19*(4), 2022-2051.

Braga, A. A., Welsh, B. C. & Schnell, C. (2015). Can Policing Disorder Reduce Crime? A Systematic Review and Meta-analysis. *Journal of Research in Crime and Delinquency, 52*(4), 567-588. https://doi.org/10.1177/0022427815576576

Fitzpatricka, D. J., Gorra, W. & Neill, D. B. (2020). Policing Chronic and Temporary Hot Spots of Violent Crime: A Controlled Field Experiment. *British Journal Criminology*, *44*(4), 296-315.

National Academies of Sciences, E. & Medicine. (2018). *Proactive Policing: Effects on Crime and Communities* (D. Weisburd & M. K. Majmundar, Eds.). The National Academies Press. https://doi.org/10.17226/24928

Novak, K., Fox, A., Carr, C. & Spade, D. (2016). The efficacy of foot patrol in violent places. *Journal of Experimental Criminology*, *12*. https://doi.org/10.1007/s11292-016-9271-1

Ratcliffe, J., Taniguchi, T., Groff, E. & Wood, J. (2011). The Philadelphia Foot Patrol Experiment: A Randomized Controlled Trial of Police Patrol Effectiveness in Violent Crime Hotspots. *Criminology*, *49*, 795-831. https://doi.org/10.1111/j.1745-9125.2011.00240.x

Telep, C., Weisburd, D., Gill, C., Vitter, Z. & Teichman, D. (2014). Displacement of crime and diffusion of crime control benefits in large-scale geographic areas: a systematic review. *Journal of Experimental Criminology*, *10*, 515-548.