Replication: 'The Distributive Politics of Enforcement'

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2/21/2020

Credit Where it is Due:

The Distributive Politics of Enforcement

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Overview:

This paper looks at police behavior in varying contexts around Latin America to explore what gets prosecuted and what is allowed to go unnoticed. The areas of interest are the relationships between constituency of the powers that be (at a given time) and how much those individuals in the constituent groups care to have property rights enforced. Involving a great deal of original research, the author does an intriguing job of addressing this question in a rather Bayesian way, so I thought this would be a good project on a topic that I briefly studied previously and can now apply new skills to.

The author argues that in many cases, not enforcing these laws is as intentional as enforcing them and makes the early assertion of one of her findings where she found a five times higher enforcement rate in places where constituents were primarily non-poor (a binary distinction make in the data analysis portion of the research). Holland uses many standardized poisson regression models, which makes sense in the setting where response variables are the topic of interest. The catch in that model is the concern for invalidation by reverse causality. To counter this point, a supply vs. demand framework is raised as one might find in your favorite introductory economics course with the y-axis showing enforcement frequency and the x-axis showing offenses. The key to this argument is in assuming that the intentional non-enforcement cases would translate to an outward shift in the 'supply curve' of enforcement. This framework gives a decent basis to analyze electoral and otherwise political behavior and regional differences. The results of the data and the proposed model seem to support this framework and initial intuition, even if it is specific to the case observed. I would have concerns about the external validity of Holland's model, but nonetheless I agree that the model results in support for the framework claiming that there is an inverse relationship between police enforcement of vending licensing and quantity of poor individuals voting in a district.

A Quote from the Abstract:

"Why do some politicians tolerate the violation of the law? In contexts where the poor are the primary violators of property laws, I argue that the answer lies in the electoral costs of enforcement: Enforcement can decrease support from poor voters even while it generates support among nonpoor voters. Using an original data set on unlicensed street vending and enforcement operations at the subcity district level in three Latin American capital cities, I show that the combination of voter demographics and electoral rules explains enforcement. Supported by qualitative interviews, these findings suggest how the intentional nonenforcement of law, or forbearance, can be an electoral strategy. Dominant theories based on state capacity poorly explain the results."[1]

-Alisha C. Holland (Holland 2014)

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[1]"All analysis and output code for this replication project as well as the original paper are available here.

Proposed Extension and Addition to Human knowledge:

Extending this academic work presents a particular challenge. The core of this research hinges on original data collected by the author through interviews and collection of data on site in Colombia, Chile, and Peru – places I have never been to nor have the means to go to now. In addition to this, there is at this point data missing from my possession that is temporal in nature. My ideal extension of this work relies on this temporal data.

As this paper was published in 2015, I would like to do an analysis of those same cities with data from the last five years. After making sure that the political and electoral systems are acceptably similar to the conditions which were posited in Holland's work, it would be great to be able to test her methods as predictive models and observe their accuracy. This opens up a discussion regardless of the congruence, as high similarity supports her arguments and her modeling work and significant differences pose any number of questions about what has changed in the political sphere in the differential city.

That said, and pending the not-insignificant chance that this data continues to be unavailable, I would like to further explore the concerns of reverse causality in this paper, either through instrumental variable regression or through the causal methods that we will cover in the near future in 1006. I was fascinated by the work and the logic in Holland's paper, but there were several points of concern that I think warrant more testing and exploration to see whether these assumptions hold or whether they are conjecture that would lead to significant differences between the model's predictions as mentioned above and reality now or in the future. In addition to this, and in the Bayesian spirit of data analysis, I think it would be interesting to look at the current data where decentralized is a binary variable and use this to look at whether this would be an informative practice in supporting Holland's original work.

As a third alternative, I am relatively familiar with OECD and health-related data sourcing. Holland showed in some ways how demographic variables were not necessarily informative to the topic of the study, but health and wellness data could be informative; especially in a setting where budget and poverty are core drivers and points of information. I do have the intuition at this point that I would still be relying on access to the temporal dataset used in the paper that is not included in the dataverse.

This is my attempted replication of one of Holland's regression tables.

The regression type is a log-likelihood regression. This regression was solely for Bogotá.

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Sun, Apr 05, 2020 - 20:03:46

<div align="center">

Table 1:

	Dependent variable:
	operations
slower	−0.053
	(0.087)
svendors	0.571***
	(0.068)
sbudget	0.038
	(0.127)
spop	0.207**
	(0.087)
Constant	1.987***
	(0.091)
Observations	19
Log Likelihood	−41.918
Akaike Inf. Crit.	93.837
Note:	*p<0.1; **p<0.05; ***p<0.01

</div>

	Bogotá
	(1)
Lower	−0.052
	(0.074)
Vendors	0.770*
	(0.091)
Budget	0.039
	(0.051)
Population	0.230*
	(0.076)
Margin	
Margin∗Lower	
Right	
Reports	
N	19
R^2	0.467

Notes: *p < 0.05; Poisson robust
ease of interpretation. Model 5 u

Figure 1: This is the Bogota section of Holland's table 2 for reference:
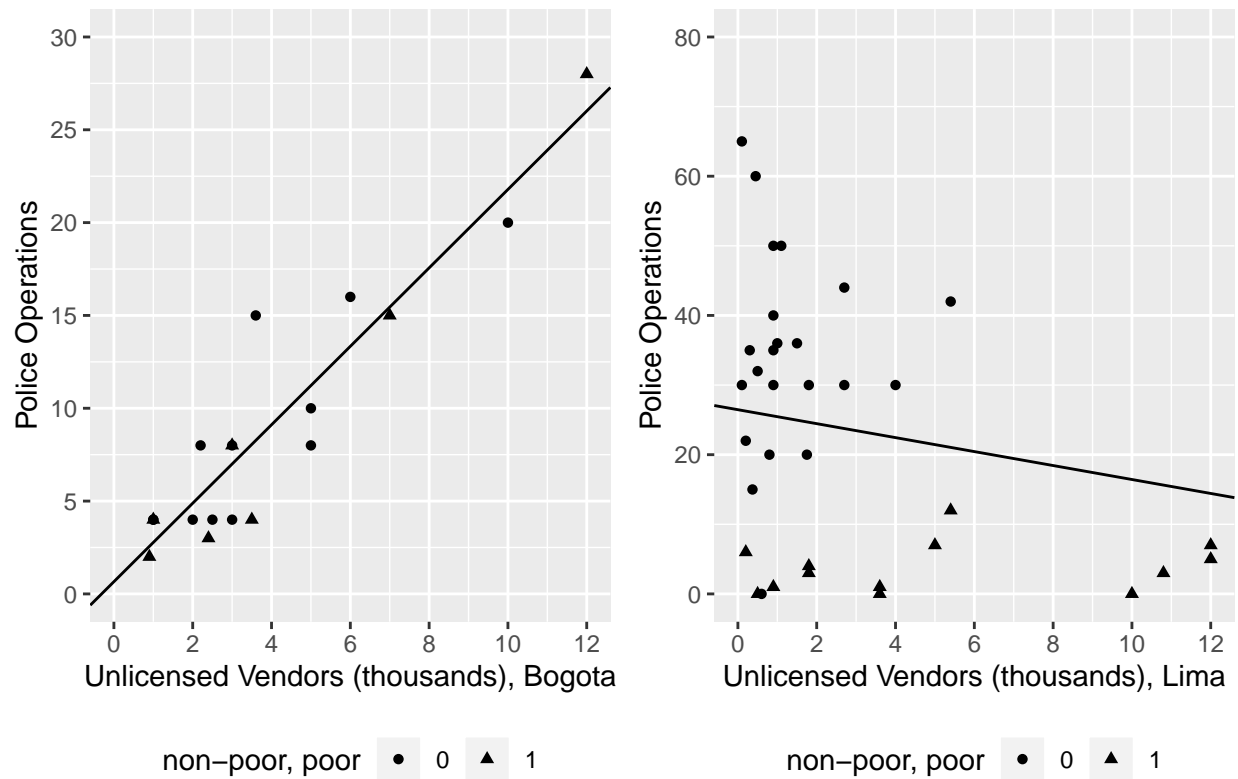
Enforcing Vendors' Licenses: Bogotá, Columbia

Data showing the association between quantity of unlicensed street
vendors and number of police operations in the area in question. A linear
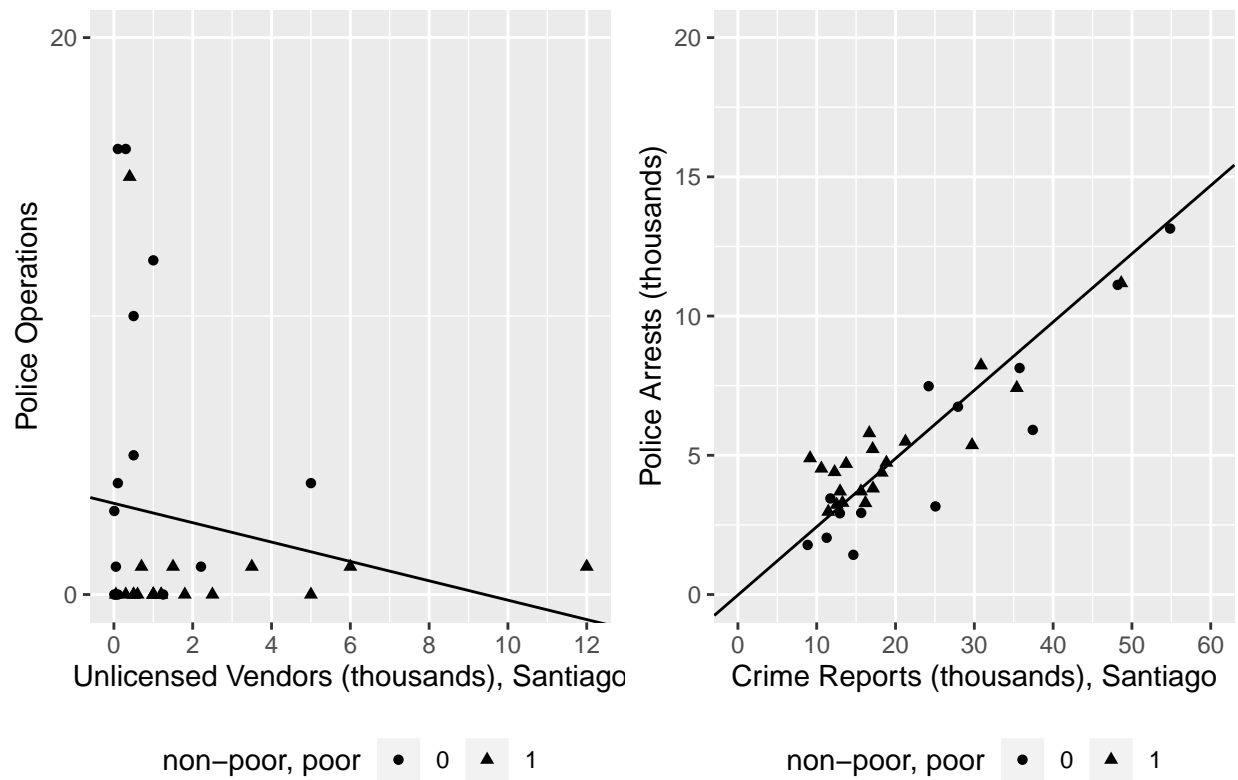regression line is included to enphasize the slope of the reationship

Poor District Binary   ●   0   ▲   1
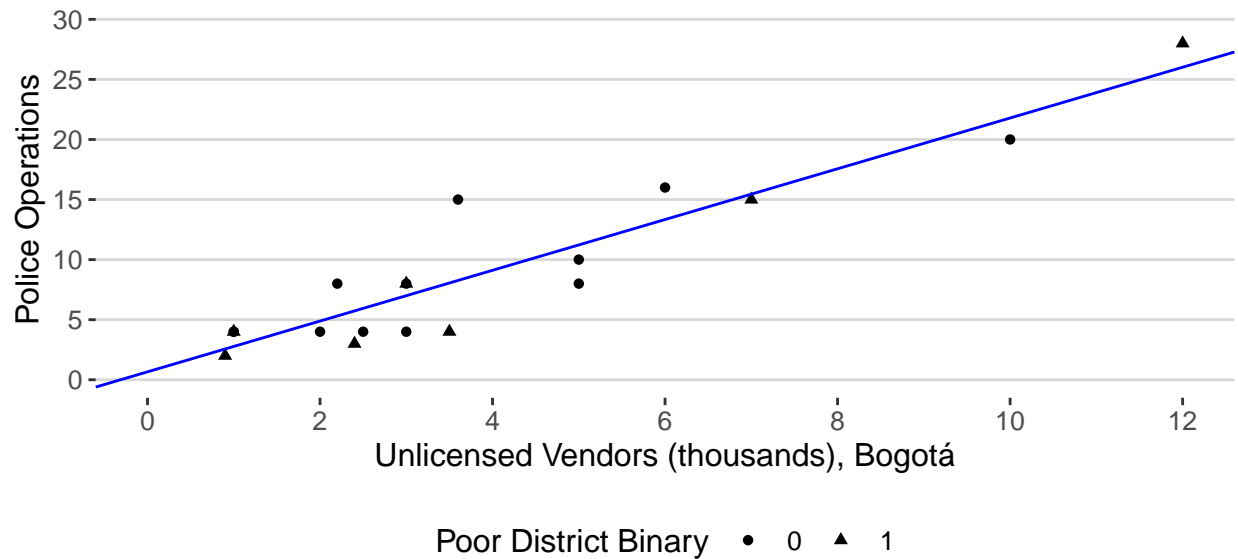
Data from original research done by Alisha C. Holland.
Find the original paper and reference to the associated
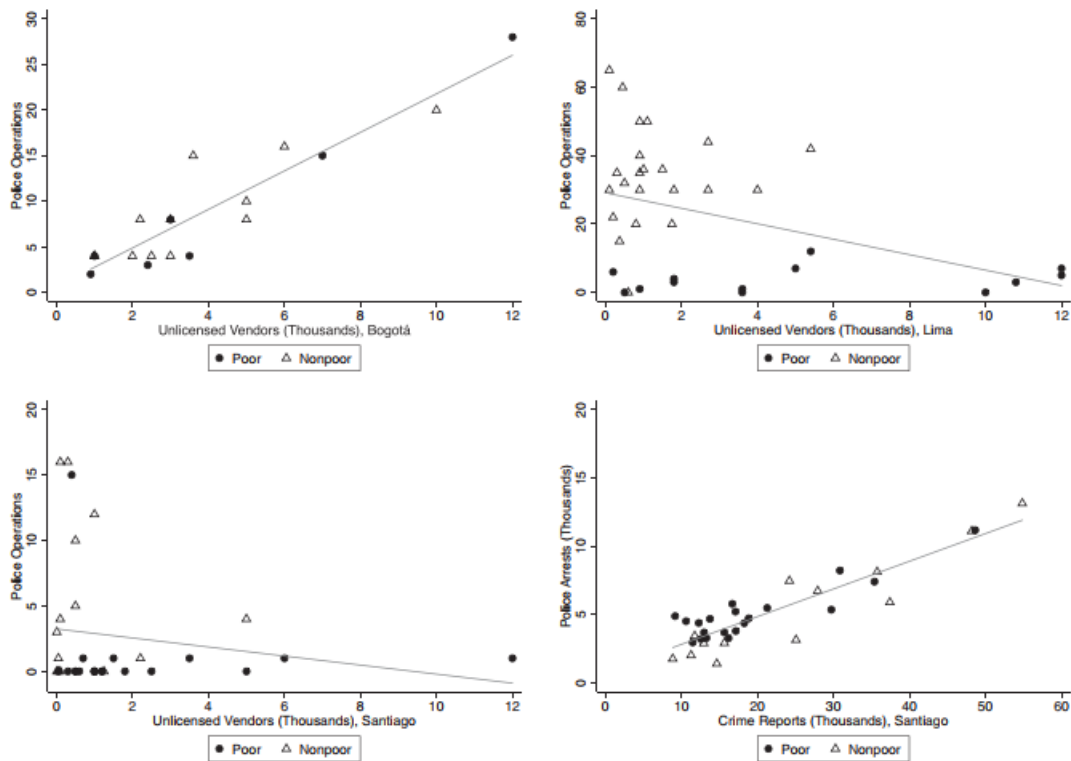dataverse at: https://doi.org/10.1111/ajps.12125

Appendix:

I was unable to recreate one graphic on account of not having access to political adn temporal data that would allow me to create teh graphic showing class gradient, budget, operations, and politicians in power for certain time frames. Otherwise, I have replicated or attempted to replicate all of the major analyses in the paper with the data I have access to. The preliminary supply/demand graphic in the paper is one made from dummy data as a means to mock up the concept in the introduction and not an analysis core to the data itself.
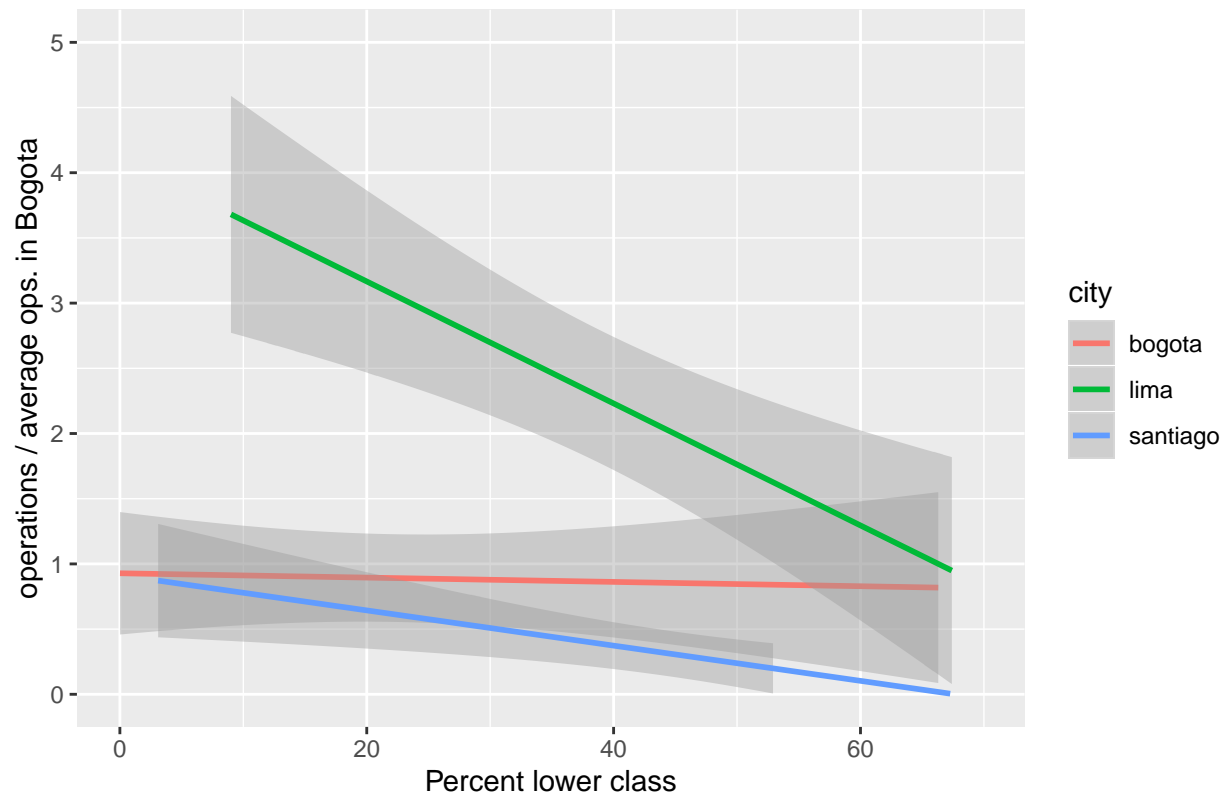
Police Operations (top left plot)
Unlicensed Vendors (thousands), Santiago
non−poor, poor ● 0 ▲ 1

Police Arrests (thousands) (top right plot)
Crime Reports (thousands), Santiago
non−poor, poor ● 0 ▲ 1

FIGURE 3 Relationships between Enforcement, Offenses, and District Poverty by City

Police Operations
Unlicensed Vendors (Thousands), Bogotá
● Poor   △ Nonpoor

Police Operations
Unlicensed Vendors (Thousands), Lima
● Poor   △ Nonpoor

Police Operations
Unlicensed Vendors (Thousands), Santiago
● Poor   △ Nonpoor

Police Arrests (Thousands)
Crime Reports (Thousands), Santiago
● Poor   △ Nonpoor

The following graphs are my closest attempt at figure 2

operations / average ops. in Bogota vs Percent lower class

city: bogota, lima, santiago

Bogota

Lima

Santiago

Holland, Alisha C. 2014. "The Distributive Politics of Enforcement." https://doi.org/10.1111/ajps.12125.

Table 2: Santiago

Dependent variable:

operations

	Bogota		Lima				Santiago		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lower	−0.053	−0.693***	−0.641***	−0.975***	−0.707***	−0.673***	−0.767***	−0.449***	−0.253
	(0.087)	(0.052)	(0.054)	(0.085)	(0.166)	(0.165)	(0.218)	(0.156)	(0.181)
Vendors	0.571***	−0.182***	−0.162**	−0.090	−0.528*	−0.683**	−0.754**	−0.496**	−0.291
	(0.068)	(0.064)	(0.064)	(0.066)	(0.290)	(0.336)	(0.364)	(0.230)	(0.223)
Budget	0.038	0.060**	0.120***	0.087***	−0.149	0.096	0.138	−0.177	0.110
	(0.127)	(0.027)	(0.029)	(0.031)	(0.122)	(0.130)	(0.145)	(0.115)	(0.142)
Population	0.207**	0.468***	0.467***	0.368***	0.272*	0.586***	0.635***	0.406**	0.173
	(0.087)	(0.054)	(0.056)	(0.060)	(0.165)	(0.186)	(0.203)	(0.181)	(0.201)
Margin			0.166***	−0.188**		−0.680***	−0.868***		
			(0.034)	(0.078)		(0.160)	(0.330)		
Margin*Lower				0.425***			0.292		
				(0.085)			(0.436)		
Right								2.083***	1.761***
								(0.412)	(0.422)
Reports									0.063***
									(0.016)
Constant	1.987***	2.920***	2.899***	2.876***	0.665***	0.461***	0.478***	−0.826**	−1.016***
	(0.091)	(0.043)	(0.044)	(0.045)	(0.139)	(0.169)	(0.169)	(0.388)	(0.386)
Observations	19	36	36	36	34	34	34	34	34
Log Likelihood	−41.918	−231.254	−220.184	−207.689	−108.395	−97.262	−97.035	−88.994	−81.850
Akaike Inf. Crit.	93.837	472.509	452.369	429.378	226.791	206.524	208.069	189.987	177.700

Note: *p<0.1; **p<0.05; ***p<0.01