

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 made 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)

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:

al;sdkfja;sldkfj;a as;dfkja;sdlfkja; adsf;lakjs;dfkajs;d as;dfkjja;slkfjd;askl

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 - 19:33:49

Table 1:	
	<i>Dependent variable:</i>
	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
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01	

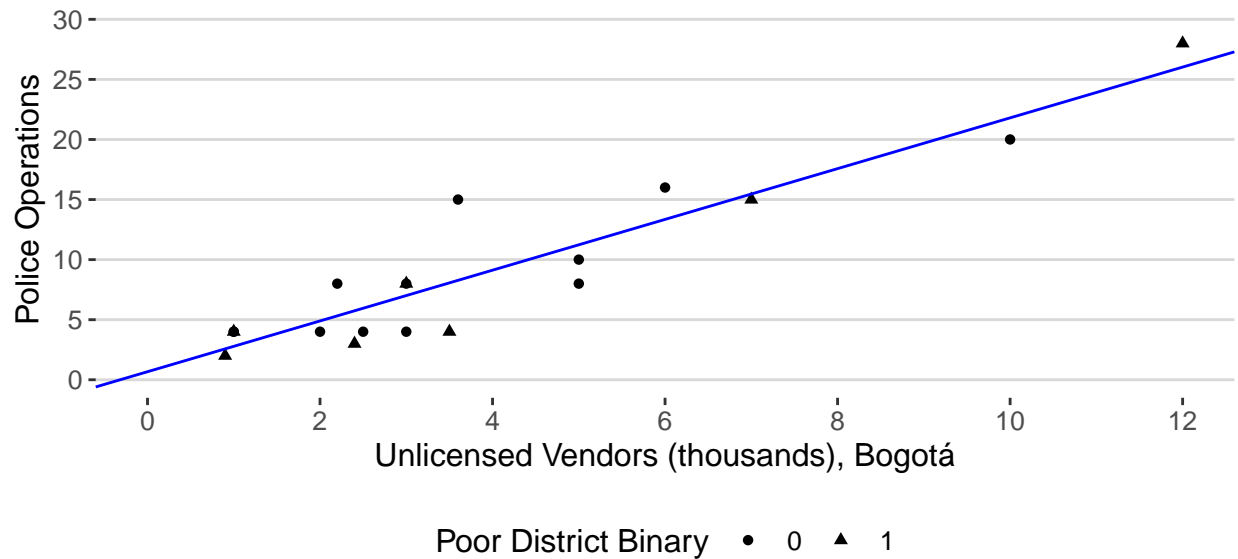
	Bogotá
	(1)
<i>Lower</i>	−0.052 (0.074)
<i>Vendors</i>	0.770* (0.091)
<i>Budget</i>	0.039 (0.051)
<i>Population</i>	0.230* (0.076)
<i>Margin</i>	
<i>Margin*Lower</i>	
<i>Right</i>	
<i>Reports</i>	
N	19
R^2	0.467
Notes: *p < 0.05; Poisson robust : ease of interpretation. Model 5 u	

Figure 1: This is the Bogota section of Holland's table 2 for reference:

“Beautiful” Graphic

Enforcing Vendors' Licenses: Bogotá, Columbia

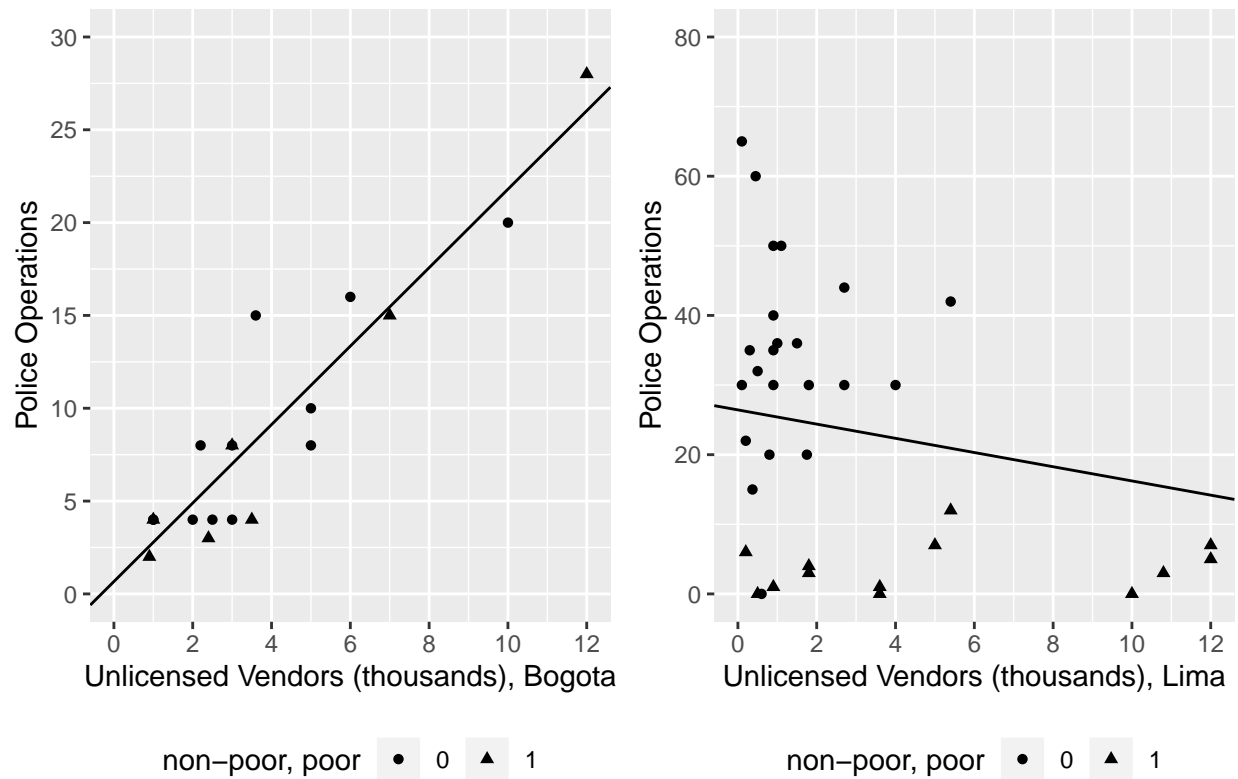
Data showing the association between quantity of unlicensed street vendors and number of police operations in the area in question. A linear regression line is included to emphasize the slope of the relationship



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 and temporal data that would allow me to create the 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.



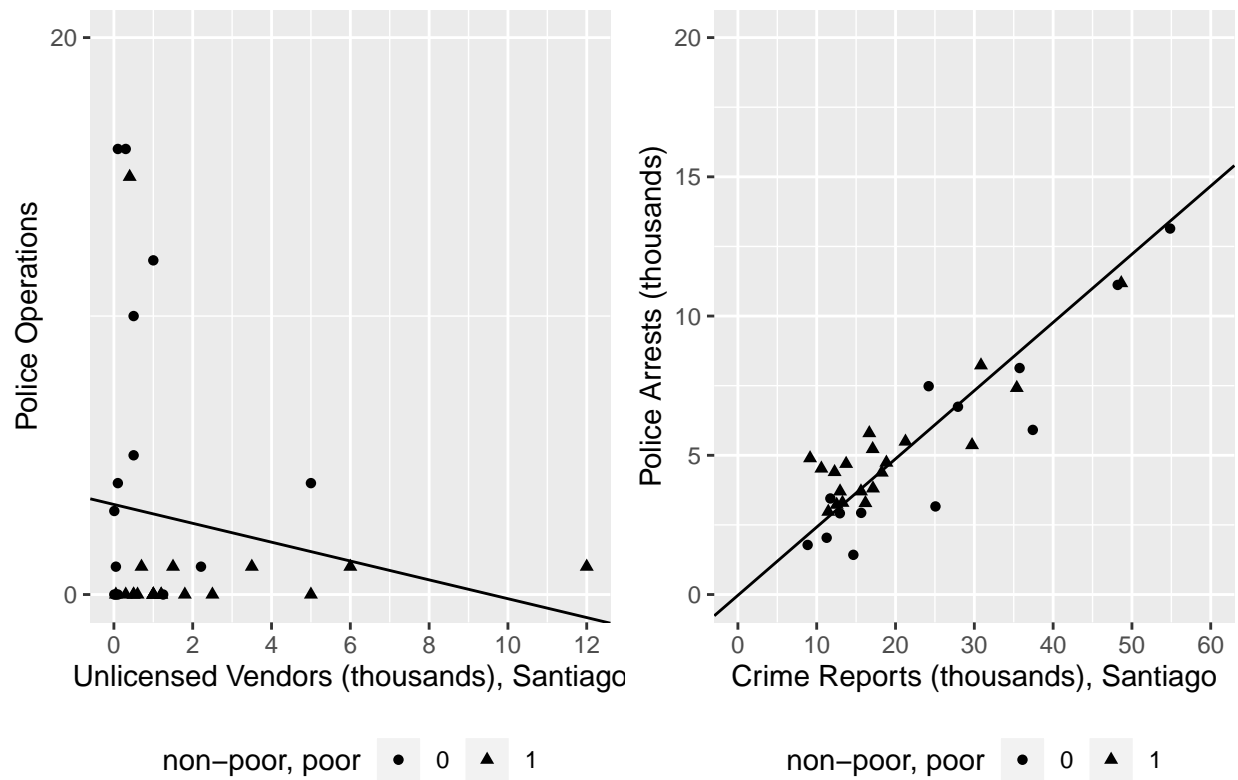
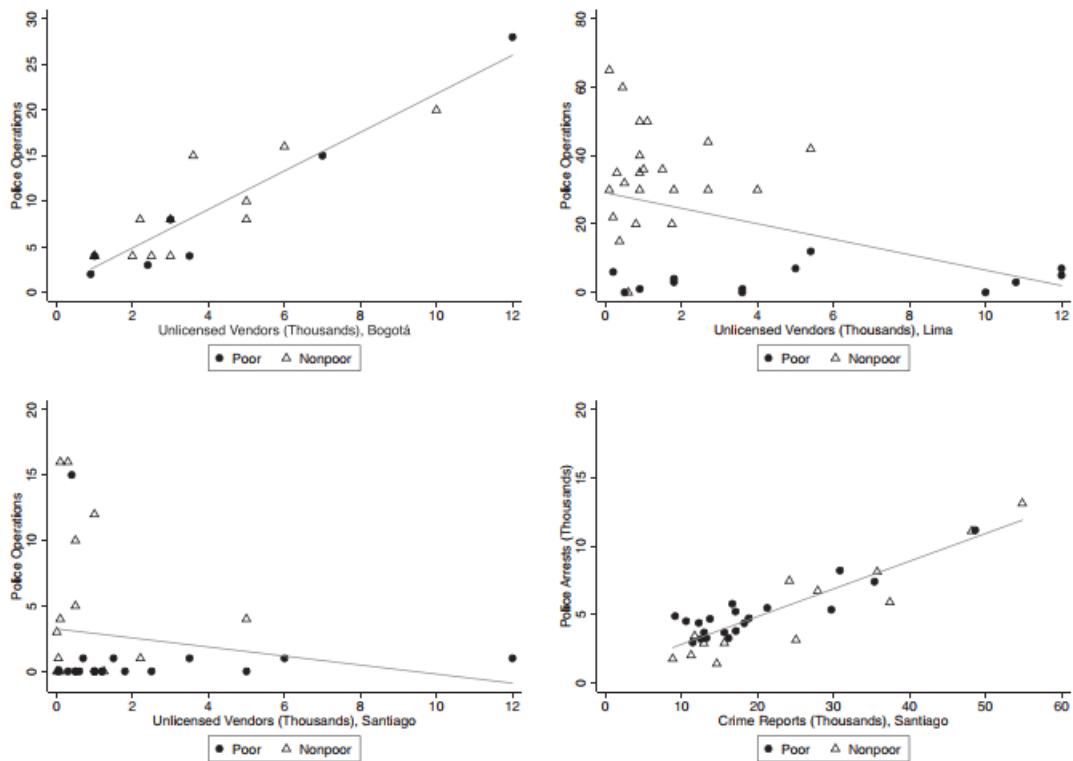
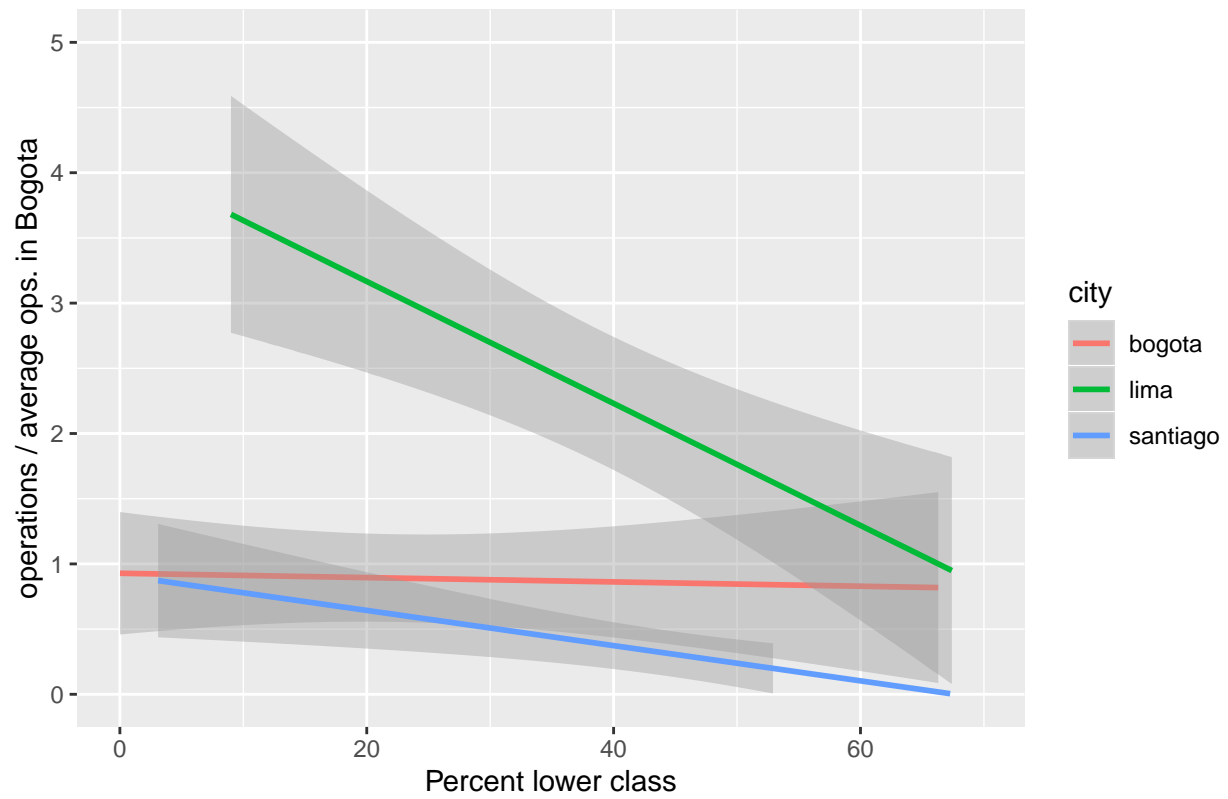
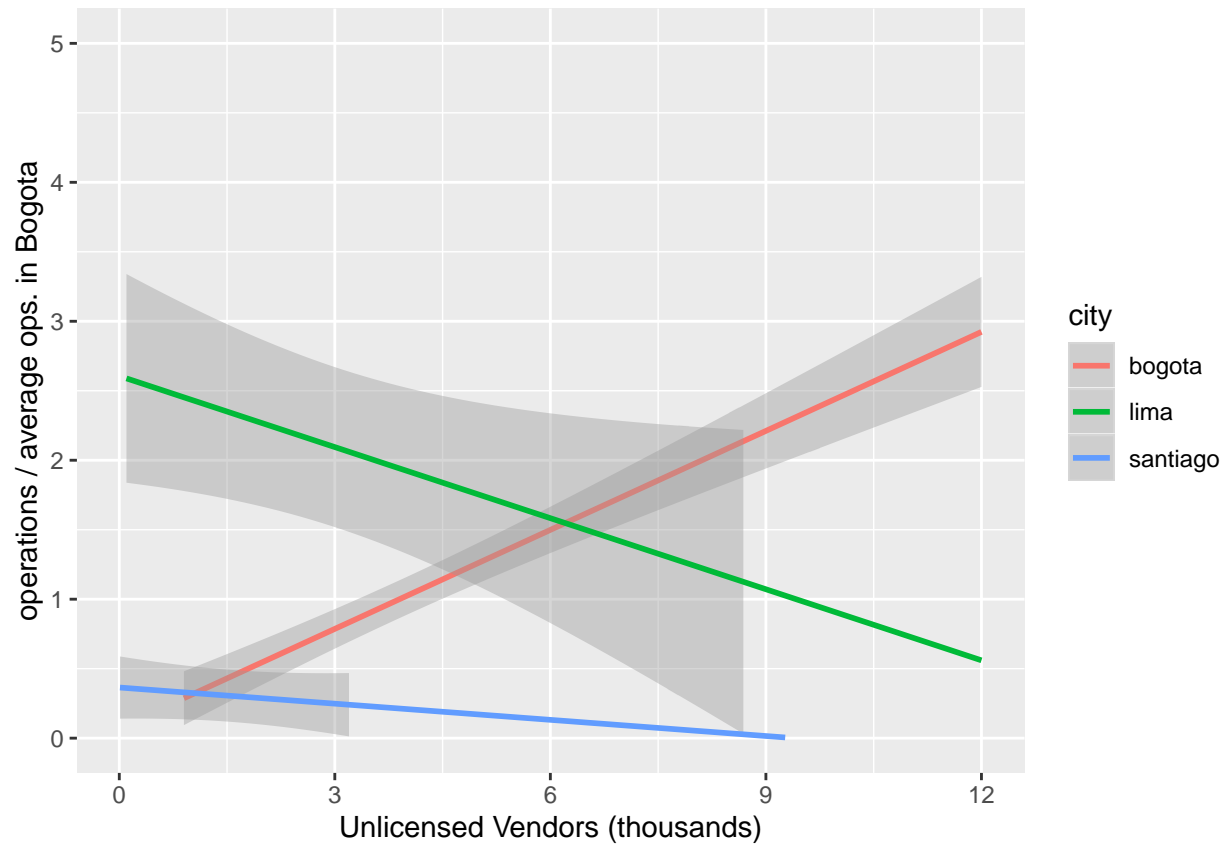


FIGURE 3 Relationships between Enforcement, Offenses, and District Poverty by City



The following graphs are my closest attempt at figure 2





Bogota

Lima

Santiago

% 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 - 19:33:53 % Requires LaTeX packages: rotating

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

Table 2: Santiago

Dependent variable:										
	Bogota			Lima			operations			Santiago
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Lower	-0.053 (0.087)	-0.693*** (0.052)	-0.641*** (0.054)	-0.975*** (0.085)	-0.707*** (0.166)	-0.673*** (0.165)	-0.767*** (0.218)	-0.449*** (0.156)	-0.253 (0.181)	
Vendors	0.571*** (0.068)	-0.182*** (0.064)	-0.162*** (0.064)	-0.090 (0.066)	-0.528* (0.290)	-0.683*** (0.336)	-0.754** (0.364)	-0.496** (0.230)	-0.291 (0.223)	
Budget	0.038 (0.127)	0.060** (0.027)	0.120*** (0.029)	0.087*** (0.031)	-0.149 (0.122)	0.096 (0.130)	0.138 (0.145)	-0.177 (0.115)	0.110 (0.142)	
Population	0.207** (0.087)	0.468*** (0.054)	0.467*** (0.056)	0.368*** (0.060)	0.272* (0.165)	0.586*** (0.186)	0.635*** (0.203)	0.406** (0.181)	0.173 (0.201)	
Margin			0.166*** (0.034)	-0.188** (0.078)		-0.680*** (0.160)	-0.868*** (0.330)			
Margin*Lower				0.425*** (0.085)			0.292 (0.436)			
Right								2.083*** (0.412)	1.761*** (0.422)	
Reports									0.063*** (0.016)	
Constant	1.987*** (0.091)	2.920*** (0.043)	2.899*** (0.044)	2.876*** (0.045)	0.665*** (0.139)	0.461*** (0.169)	0.478*** (0.169)	-0.826** (0.388)	-1.016*** (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