

Replication: ‘The Distributive Politics of Enforcement’

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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 (what I believe is) 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.

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.”

-Alisha C. Holland (Holland 2014)

```
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   city = col_character(),
##   district = col_character()
## )

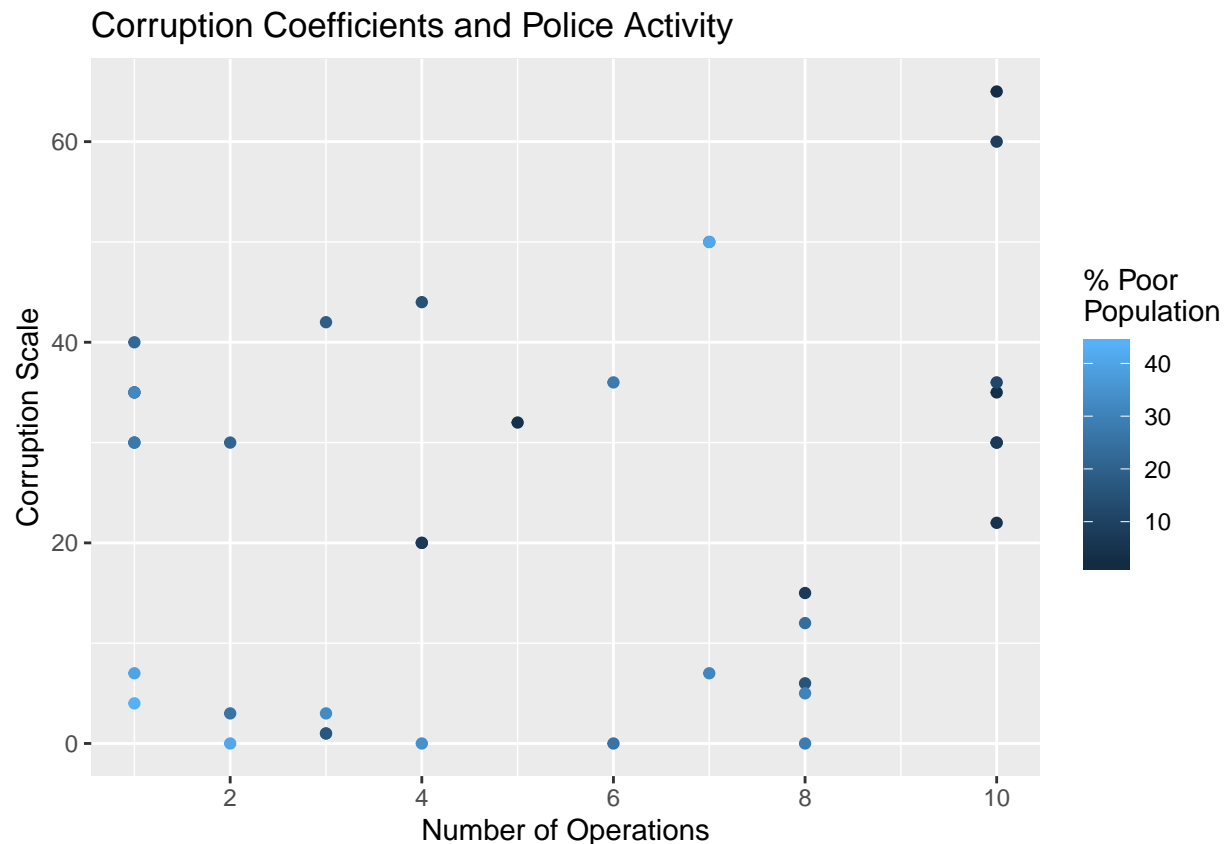
## See spec(...) for full column specifications.
```

My work has been documented and logged on github.¹

¹Check Out My Repo Here!

Initial Data Exploration

```
## Observations: 89
## Variables: 21
## $ city      <chr> "santiago", "santiago", "santiago", "santiago", "santi...
## $ district  <chr> "Cerrillos", "Cerro Navia", "Conchalí", "El Bosque", "...
## $ operations <dbl> 0, 0, 0, 0, 12, 0, 0, 0, 1, 1, 0, 10, 1, 5, 0, 0, 4...
## $ lower     <dbl> 52.2, 69.8, 54.8, 58.4, 43.6, 58.3, 41.0, 38.3, 36.7, ...
## $ vendors   <dbl> 0.50, 0.60, 5.00, 1.20, 1.00, 0.30, 0.05, 1.25, 2.21, ...
## $ budget    <dbl> 337.24, 188.87, 210.71, 153.76, 264.43, 430.42, 312.75...
## $ population <dbl> 6.6160, 13.3943, 10.7246, 16.8302, 11.1702, 8.5761, 5....
## $ margin     <dbl> 39.02, 12.76, 1.72, 8.90, 4.81, 22.62, 16.82, 18.08, 5...
## $ right      <dbl> 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, ...
## $ arrests    <dbl> 3.295, 4.525, 5.226, 5.796, 6.743, 3.225, 2.933, 3.163...
## $ reports    <dbl> 13.269, 10.591, 17.100, 16.673, 27.925, 12.535, 15.645...
## $ poordistrict <dbl> 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, ...
## $ costs      <dbl> 3, 1, 1, 2, 7, 1, 1, 10, 1, 3, 1, 8, 10, 10, 3, 1, 10,...
## $ corruption <dbl> 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 5, 10, 10, 10,...
## $ constraint <dbl> 10, 8, 1, 5, 3, 10, 10, 10, 1, 1, 10, 3, 10, 3, 1, 1, ...
## $ poor       <dbl> 8.5, 18.2, 11.6, 13.8, 9.6, 16.9, 8.6, 12.3, 9.7, 23.2...
## $ police     <dbl> 3, 1, 4, 2, 4, 1, 7, 3, 4, 3, 2, 1, 3, 2, 4, 1, 1, 3, ...
## $ employees  <dbl> 3.51, 1.96, 2.84, 1.82, 3.62, 2.85, 4.13, 3.68, 1.24, ...
## $ tax        <dbl> 14.50670, 1.59465, 6.95896, 2.36865, 10.74250, 23.3486...
## $ salary     <dbl> 13866.539, 13086.474, 11668.783, 13988.493, 11525.394,...
## $ vendorsalt <dbl> 0.433, 0.891, 2.756, 2.342, 0.858, 0.377, 0.081, 0.440...
```



An Interesting Chart of Average Arrest Rates per District in Santiago, Chile

I am unsure what's going on with Santiago, Santiago, but that is a question for later.

Average Per Capita Arrest Rate per District
Districts from the city of Santiago

District	Arrest Rate
Santiago	170.70%
Estacion Central	60.40%
San Ramon	58.30%
Independencia	57.20%
Nunoa	51.60%
Cerrillos	49.80%
Conchali	48.70%
Lo Espejo	47.40%
La Cisterna	44.30%
Recoleta	43.00%
San Miguel	41.10%
Lo Prado	40.40%
Pedro Aguirre Cerda	39.90%
San Joaquin	38.50%
Quinta Normal	37.80%
Huechuraba	37.60%
Renca	36.20%
La Granja	35.60%
Macul	35.30%
El Bosque	34.40%
Cerro Navia	33.80%
La Florida	33.00%
Providencia	30.30%
Pudahuel	27.60%
San Bernardo	26.50%
Penalolen	22.10%
La Reina	21.30%
Las Condes	20.50%
Quilicura	20.50%
La Pintana	18.80%
Vitacura	17.90%
Lo Barnechea	16.20%
Puente Alto	15.20%
Maipu	13.10%

Regression Table Attempt

Stata would be nicer most likely, but here goes... The data used can be found in my github repo (Meche 2020).

All regressions are prediction models of the number of police operations, in this case all operations in lima. Particularly interesting is the regression (4), where the glm regression predicts a decrease of ≈ 28 operations on average when the district is poor vs. when it is not... things seem to change when the core constituency changes.

```
##
## =====
##                               Dependent variable:
##                               -----
##                               operations
##                               OLS
##                               (1)          (2)          (3)          (4)      normal
## -----
## vendors          -1.019          0.818          0.855
##                  (0.704)        (0.664)        (0.657)
##
## lower            -0.635***        -0.588***
##                  (0.131)        (0.134)
##
## budget                                0.008
##                                      (0.006)
##
## poordistrict                                -28.182***
##                                      (4.370)
##
## Constant          26.522***        45.501***        41.515***        34.182***
##                  (3.834)        (4.910)        (5.710)        (2.725)
## -----
## Observations          36          36          36          36
## R2                    0.058          0.451          0.479
## Adjusted R2          0.030          0.417          0.430
## Log Likelihood
## Akaike Inf. Crit.
## Residual Std. Error 18.498 (df = 34) 14.339 (df = 33) 14.177 (df = 32)
## F Statistic         2.095 (df = 1; 34) 13.535*** (df = 2; 33) 9.817*** (df = 3; 32)
## =====
## Note:                                     *p<0.1; **p<0.05; ***p<0.01
```

Appendix:

```
##
## *****

## Note: As of version 1.0.0, cowplot does not change the

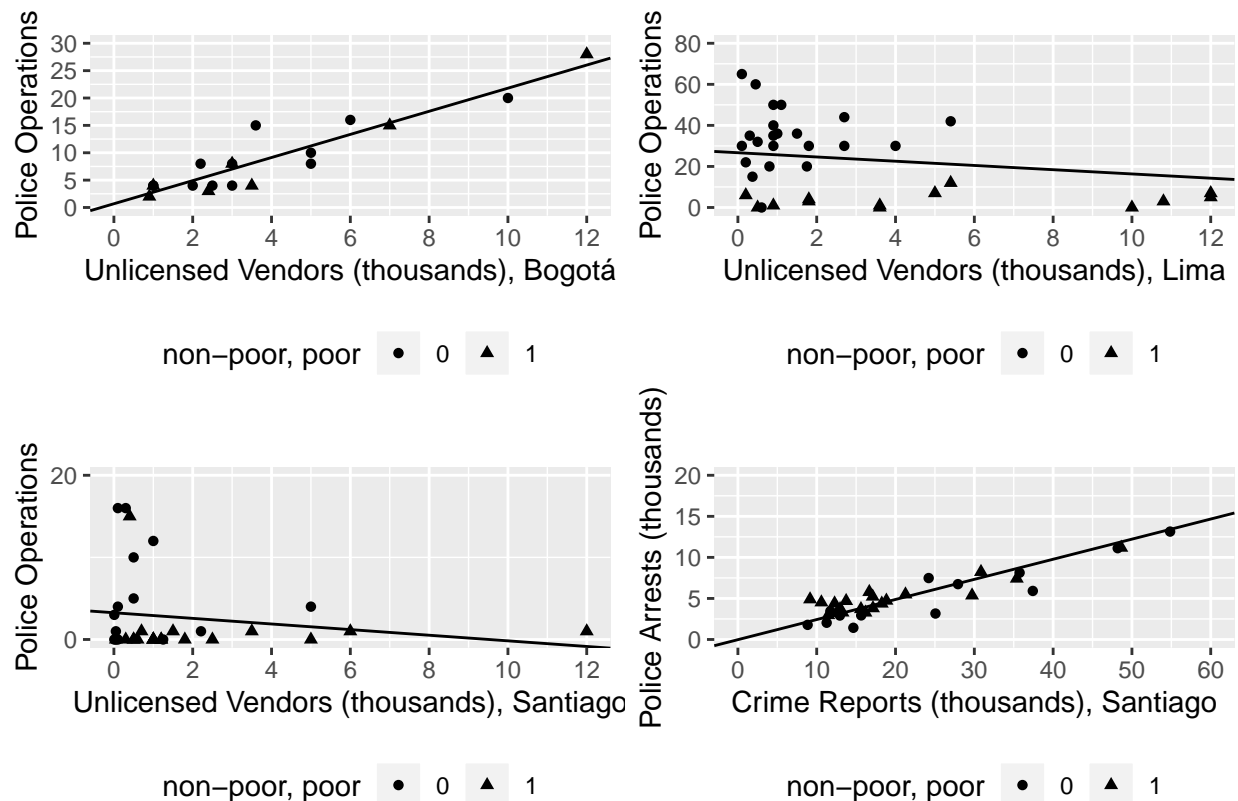
## default ggplot2 theme anymore. To recover the previous

## behavior, execute:
## theme_set(theme_cowplot())

## *****

##
## Attaching package: 'cowplot'

## The following object is masked from 'package:ggthemes':
##
## theme_map
```



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

Meche, Beau. 2020. “Replication: The Distributive Politics of Enforcement.” https://github.com/BeauMeche/enforcement_distribution_electorate.

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

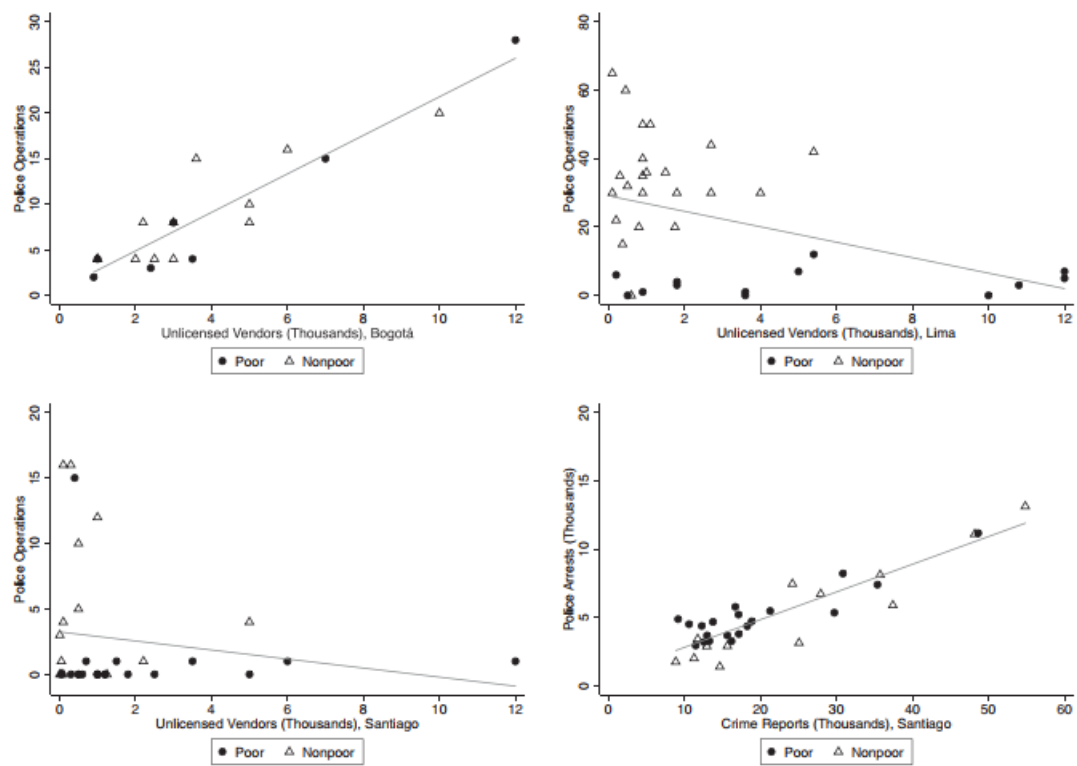


Figure 1: This is Holland's Figure 3 for reference: