# 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:**

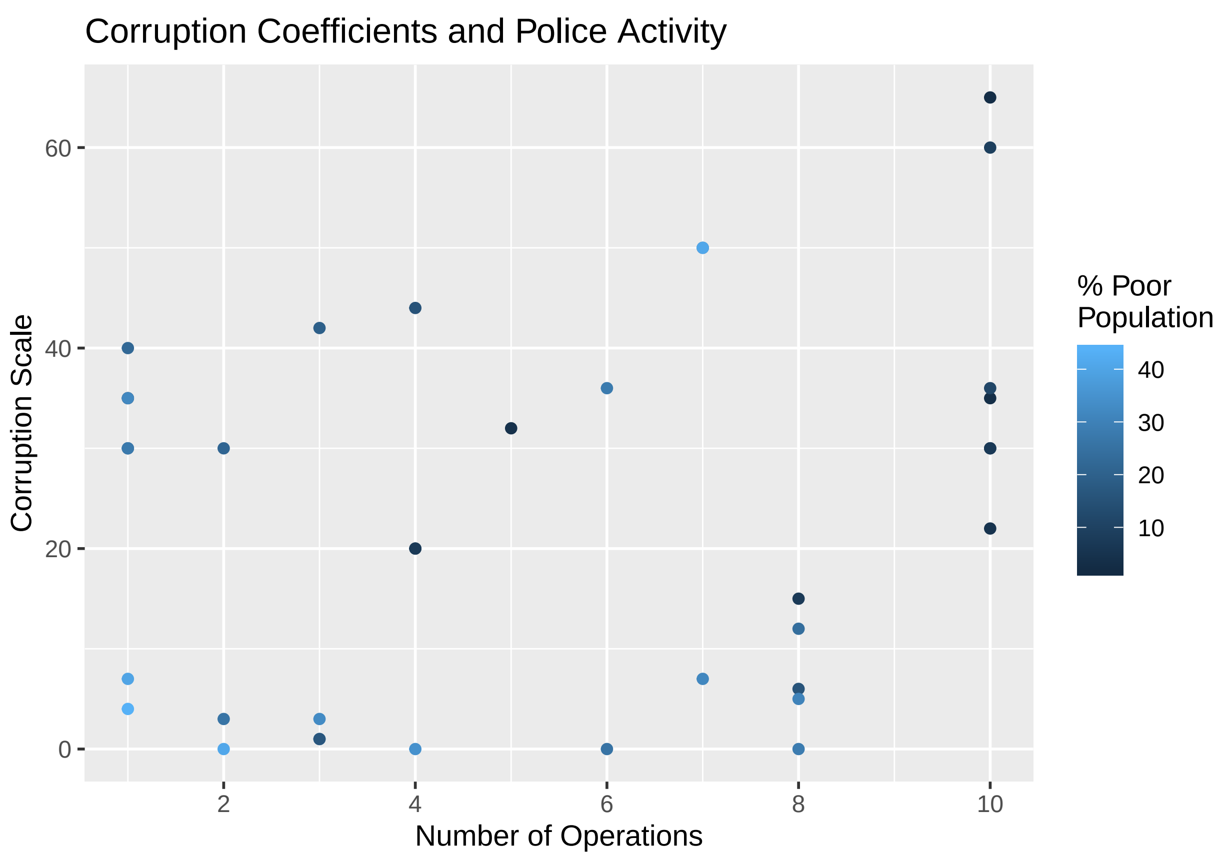
"Why do some politicians tolerate the violation of the law? In contexts where the poor are the primary violators of property laws, I argue that the answer lies in the electoral costs of enforcement: Enforcement can decrease support from poor voters even while it generates support among nonpoor voters. 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."[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.

**Initial Data Exploration**

```
## Observations: 89
## Variables: 21
## $ city        <chr> "santiago", "santiago", "santiago", "santiago", "santi...
## $ district    <chr> "Cerrillos", "Cerro Navia", "Conchali", "El Bosque", "...
## $ operations  <dbl> 0, 0, 0, 0, 12, 0, 0, 0, 1, 1, 0, 10, 1, 5, 0, 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, 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, 5, 10, 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).

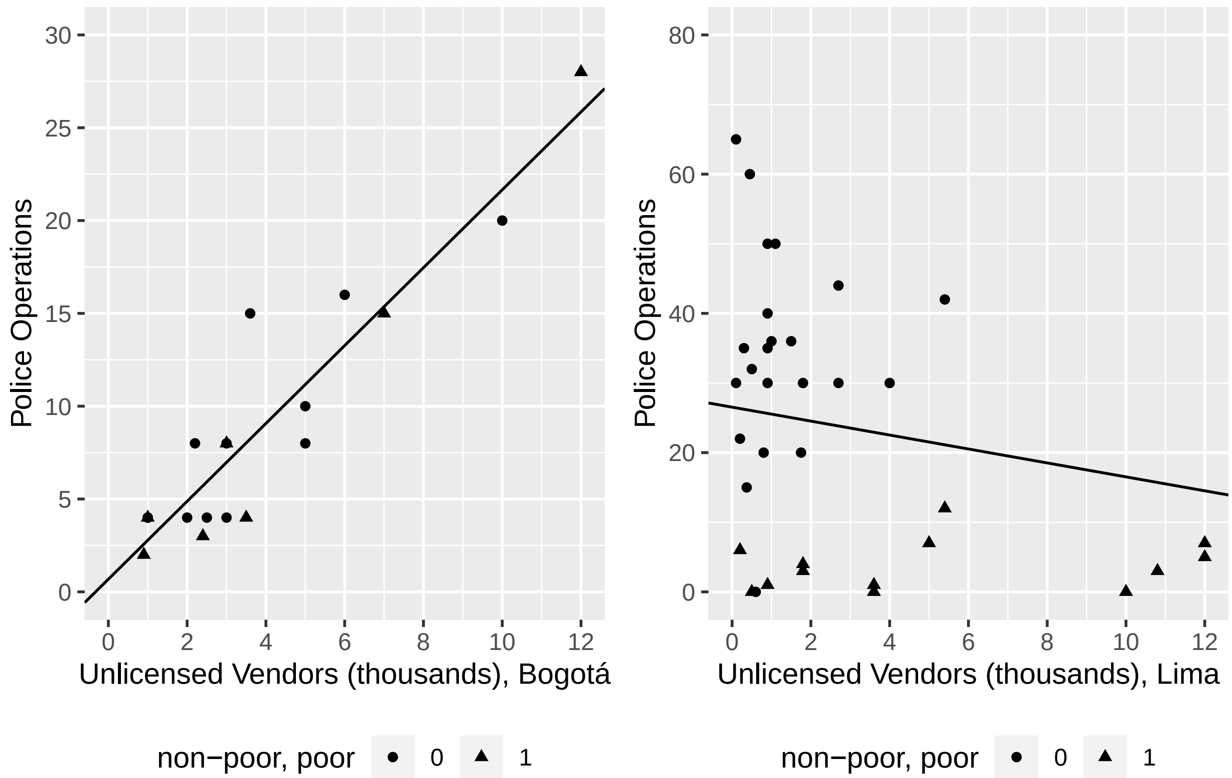
All regressions are prediction models of the number of police operations, in this case all operations in lima. Particularly interesting is the regression (4), where the glm regression predicts a decrease of $\approx 28$ operations on average when the district is poor vs. when it is not... things seem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

```
##
## ===============================================================================================
##                                                   Dependent variable:
##                         -----------------------------------------------------------------------
##                                                       operations
##                                                          OLS                                      normal
##                                (1)                    (2)                     (3)             (4)
## -----------------------------------------------------------------------------------------------
## 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                                                                              -142.783
## Akaike Inf. Crit.                                                                           289.567
## 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
```

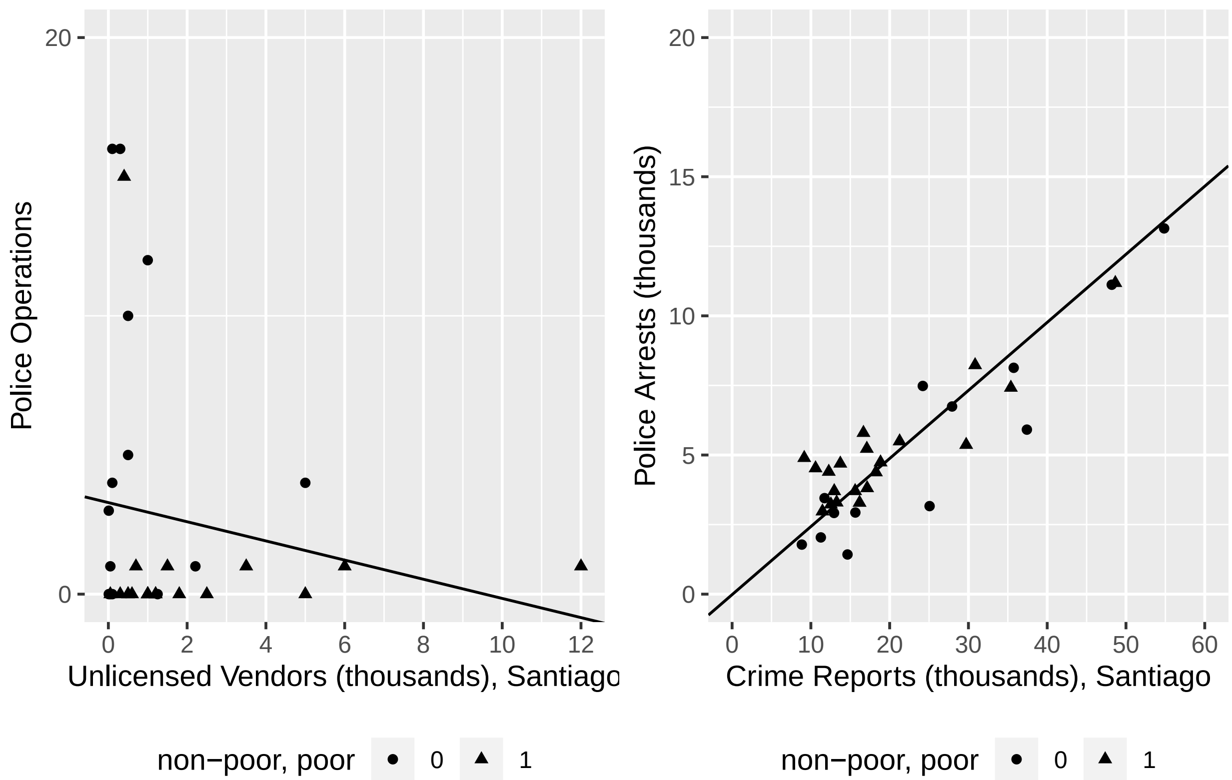
```
##
## =============================================
##                       Dependent variable:
##                   ---------------------------
##                           operations
## ---------------------------------------------
## slower                      -0.053
##                             (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
```

**Appendix:**



Police Operations
Unlicensed Vendors (thousands), Bogotá
non−poor, poor
0
1
Police Operations
Unlicensed Vendors (thousands), Lima
non−poor, poor
0
1




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**

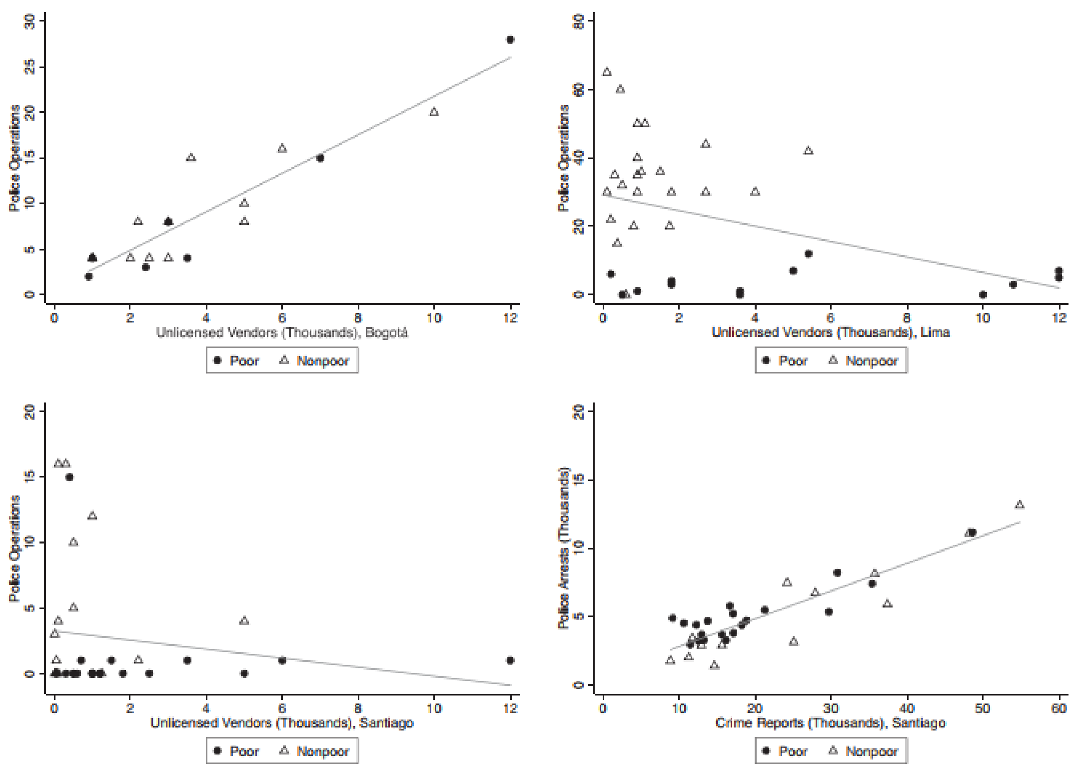



Figure 1: This is Holland's Figure 3 for reference: