Neighbourhood-level Crime Deterrence in Mexico City

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Roadmap

Introduction

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Introduction

- Crime is costly to society (Becker, 1968).
- Incentives matter: we can deter crime by increasing its expected cost.
- Society has traditionally implemented strong punishments in the form of longer sentences (incapacitation or incarceration).
- This strategy has diminishing returns and substantial costs.
- So, what if punishment can be more certain instead of longer or harsher?
- One the most commonly implemented deterrence tools is surveillance cameras.
- Evidence of the *camera deterrence effect* is mixed.
- This paper investigates the *camera deterrence effect* in Mexico City and finds that surveillance cameras do not significantly deter crime.

Related Literature

- Evidence is mixed; surveillance cameras might only deter certain crimes (McLean et al., 2013; Piza, 2018; Gomez-Cardona et al., 2017; Munyo and Rossi, 2020; Gerell 2016)
- Security agencies select the locations for deploying Closed Circuit Television (CCTV) systems.
- The literature has employed different methods: *diff-in-diff* (Gomez-Cardona et al.,2017; Munyo and Rossi, 2020), *interrupted time series analysis* (McLean et al. ,2013), *propensity score matching* (Piza, 2018), or *randomized control trials* (Hayes and Downs,2011; La Vigne and Lowry,2011).
- The crimes studied follow the FBI Uniform Crime Reporting (UCR) categories, or construct crime categories closely related to those.

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Contribution

My paper contributes in the following ways:

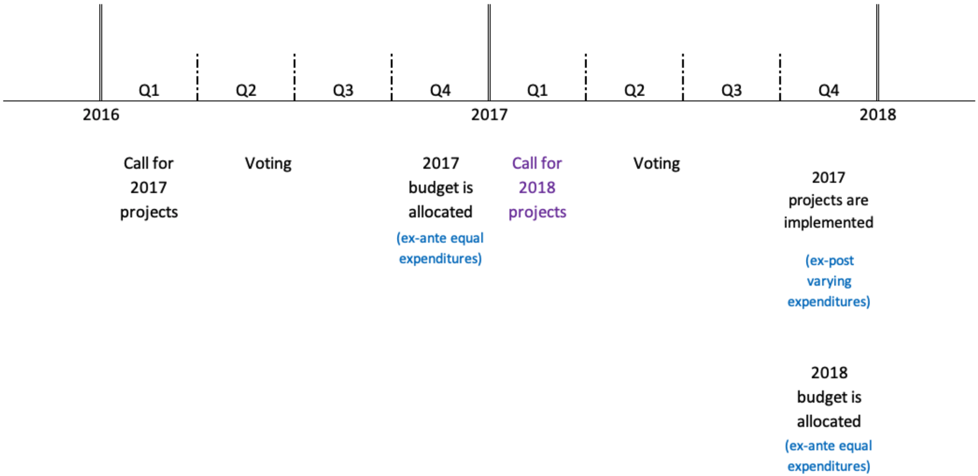
1. I construct a novel dataset containing neighbourhood-level crime rates and observable characteristics, finance data, policy intervention data.
2. I analize an environment where the location decision is not done by security agencies, but through a public program.
3. I develop a different identification strategy that allows me to recover the causal effect of the surveillance cameras' deployment.
4. I study new crime categories leveraging the greater granularity of the data available in addition to the FBI Uniform Crime Reporting (UCR) categories.
5. This is the first paper that studies the camera deterrence effects in Mexico City.

The Participatory Budget Program

- Mexico City is divided into 16 delegations (similar to boroughs),[1] and within each delegation there is a varying number of neighbourhoods.
- I study the **Participatory Budget (PB)** program. General Categories
- By law, each delegation should devote 3% of their yearly budgets to execute the winning projects.
- The winning projects, within any delegation, should be implemented with ***ex-ante* equal resources** for all areas. I will refer to this amount as *'planned expenditure.'*
- Fiscal documents show that there are ***ex-post* varying levels of expenditure** per neighbourhood. I will refer to this final amount as *'actual expenditure.'*.

[1]For example, New York City is comprised of five boroughs: The Bronx, Brooklyn, Manhattan, Queens, and Staten Island.

Timing of the PB Program



The Participatory Budget Program

- The *planned expenditure* is not observed by the neighbourhoods' inhabitants at the time of voting.
- Neighbourhoods' inhabitants do not receive the *'actual expenditure'* amounts.
- If a neighbourhood project is fully executed with an *'actual expenditure'* lower than their entitled amount (*'planned expenditure'*), the neighbourhood does not receive the remaining amount for other projects.
- Delegations are not allowed to change the projects for a neighbourhood.
- Neighbourhoods are not restricted to vote or propose projects by past decisions.

Data

The novel dataset developed for this paper contains the following information:

- Geocoded crimes at the street and neighbourhood level, with great granularity in the type of crimes reported
- Neighbourhood-level observables: population, education, unemployment, access to social security, male-headed households, the number of firms categorized by two-digit North America Industry Code System (NAICS)
- Detailed information of the Participatory Budget program
- Fiscal data on the expenditures of the winning projects by neighbourhood

The period of study is January 2016–March 2020 for 1,805 neighbourhoods.

Surveillance Cameras in Mexico City

- I will focus on the neighbourhoods where surveillance cameras are the winning project in the PB program.
- I only observe the *'actual expenditure'* associated with the cameras, not their location.
- Mexico City also has a publicly-funded CCTV system (*'government cameras'* henceforth) throughout the city installed in two stages: 2009–2012 and 2014–2016.
- The current *government cameras* stock consists of 15,000 cameras, which I geolocate at the street and neighbourhood level.
- Complementarity between these two systems.

Identification

- Data inspection shows that the *'actual expenditure'* employed by the delegation governments to implement the winning projects is different to the *'planned expenditure.'*

- This feature is not explained in any document or by any institutional rule.

- For those neighbourhoods that choose cameras, it is possible to argue that there is potential endogeneity between the crime rate in a neighbourhood and the *'actual expenditure'* it receives.

- My identification strategy is based on the assumption that **conditional on cameras being the winning option, the neighbourhood observable characteristics, the *'actual expenditure'* is as good as random.**

Identification Strategy

- Let i denote a neighborhood, and t denote the quarter.
- The regression equation is:

$$\underbrace{Y_{i,t}}_{\text{Crime counts}} = \alpha + \underbrace{\beta_0 AE_{i,t}}_{\text{Actual Expenditure}} + \beta_1 1[Cameras_{i,t}] + \underbrace{X_i'\gamma}_{\text{Neighborhood characteristics}} + \underbrace{\phi TC_t}_{\text{Stock of cameras}} + \lambda_t + \lambda_j + \varepsilon_{i,t} \quad (1)$$

where $1[Cameras_{i,t}]$ is an indicator variable for a neighbourhood choosing cameras, λ_j are delegation fixed effects, and λ_t are quarter fixed effects.

- Identifying assumption: **conditional independence assumption/selection on observables**

$$E[Y_{i,t}|1[Cameras_{i,t}] = 1, X_i, \lambda_t, \lambda_j, TC_t] = E[Y_{i,t}|1[Cameras_{i,t}] = 1, X_i, \lambda_t, \lambda_j, TC_t, AE_{i,t}]$$

Balance Tests

To support this assumption, I calculate a difference in means tests for the neighbourhood observables for the areas that vote for cameras.

The balance tests are done as follows:

1. I calculate the ratio of *'actual expenditure'* to *'planned expenditure'* for every neighbourhood that voted for cameras, and call this the *'expenditure ratio.'* I sort this *'expenditure ratio'* and calculate its median.

2. I run a regression for each neighbourhood covariate against a full set of delegation dummies and calculate the residuals

3. I then separate the neighbourhood sample into two groups: those with an *'expenditure ratio'* below the median and those with an *'expenditure ratio'* above the median.

4. With these two subgroups, I test for equality of means by employing the residuals from each covariate's regression.

This procedure is equivalent to testing for balance in the observable neighbourhood characteristics, and provide evidence that, conditional on these characteristics, the *'actual expenditure'* is as good as random.

Balance test - observables

Table 1. Neighbourhood characteristics balance test - equality of means.

	Mean				
	Whole sample (1)	Ratio below the median (2)	Ratio above the median (3)	Difference (4)	t-statistic (5)
Population	-.0000158	-40.62072	42.83462	-83.45534	-0.2807
	(148.528)	(206.8562)	(213.6248)	(297.3635)	(0.7790)
Population aged 15 and older	1.00e-08	.037926	-.0398133	.0777394	0.2325
	(.1677111)	(.2530533)	(.2184883)	(.3343249)	(0.8162)
Unemployed population	-2.49e-09	-.0101918	.010699	-.0208907	-0.2008
	(.0519077)	(.0709305)	(.076085)	(.1040195)	(0.8409)
Population with access to social security	5.08e-08	.027989	-.0293817	.0573707	0.1256
	(.2282438)	(.3211762)	(.3247353)	(.4567353)	(0.9001)
Male-headed households	2.91e-08	.0713638	-.074915	.1462788	0.4567
	(.1601442)	(.2268597)	(.2261346)	(.3203157)	(0.6480)
Total cameras per capita	-3.79e-07	-1.033603	1.085037	-2.11864	-0.2581
	(4.13509)	(6.676262)	(4.774856)	(8.208028)	(0.7964)
Planned expenditure per capita	-3.27e-08	.2929574	-.3090003	.6019577	0.6285
	(.4885509)	(.8997466)	(.3282825)	(.9577648)	(0.5299)
Actual expenditure per capita	1.13e-08	-1.299813	1.370993	-2.670806	-4.4757***
	(.3045008)	(.4905664)	(.3397707)	(.5967408)	(0.0000)

Standard errors in parentheses for columns (1)–(4), p-value for column (5)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Pre-treatment Crime Rates

Table 2. Pretreatment FBI index crimes' rates - equality of means.

	Mean				
	Whole sample (1)	Ratio below the median (2)	Ratio above the median (3)	Difference (4)	t-statistic (5)
Criminal homicide	2.92e-08	-.2196024	.2327642	-.4523666	-0.9920
	(.2307162)	(.3808246)	(.2508807)	(.4560357)	(0.3213)
Rape	-7.10e-08	-.0348618	.0369511	-.0718129	-0.0604
	(.6042938)	(1.060156)	(.536137)	(1.188013)	(0.9518)
Robbery	2.16e-07	-5.523857	5.854926	-11.37878	-2.3021*
	(2.588323)	(4.109844)	(3.050478)	(5.118226)	(0.0214)
Aggravated assault	-5.88e-08	-.3696015	.3917532	-.7613546	-0.7199
	(.536019)	(.904104)	(.5487115)	(1.057586)	(0.4717)
Part I Violent crimes	3.23e-07	-6.147921	6.516394	-12.66431	-2.1617*
	(2.962786)	(4.822888)	(3.326126)	(5.858614)	(0.0307)
Larceny-theft	2.49e-07	-4.578182	4.852573	-9.430755	-1.0281
	(4.651725)	(7.885247)	(4.686565)	(9.172841)	(0.3040)
Burglary (breaking or entering)	5.75e-09	-5.391799	5.714953	-11.10675	-0.4911
	(11.60193)	(22.02572)	(5.129281)	(22.61508)	(0.6234)
Motor vehicle theft	1.65e-07	-.5110742	.5417054	-1.05278	-0.4739
	(1.124396)	(1.869715)	(1.199535)	(2.221423)	(0.6356)
Part I Property crime	9.22e-07	-10.48105	11.10923	-21.59029	-0.7417
	(14.89729)	(27.66018)	(9.073973)	(29.11052)	(0.4584)

Standard errors in parentheses for columns (1)–(4), p-value for column (5)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Pre-treatment Crime Rates

Table 3. Pretreatment FBI index crimes' rates - equality of means.

	Mean				
	Whole sample (1)	Ratio below the median (2)	Ratio above the median (3)	Difference (4)	t-statistic (5)
Vandalism	1.08e-07	.5963025	-.6320412	1.228344	0.6727
	(.9270759)	(1.593562)	(.8915294)	(1.825997)	(0.5012)
Disorderly conduct	1.20e-09	.1810021	-.1918503	.3728524	1.0305
	(.1856315)	(.3519678)	(.0839161)	(.3618332)	(0.3030)
Drug abuse violations	5.04e-08	-1.934168	2.050092	-3.98426	-1.4478
	(1.456392)	(2.595572)	(1.179984)	(2.851203)	(0.1478)
Part II Crimes	2.91e-07	-1.156864	1.2262	-2.383064	-0.6770
	(1.790911)	(3.146544)	(1.57786)	(3.5199977)	(0.4985)

Standard errors in parentheses for columns (1)-(4), p-value for column (5)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

▸ Additional crime categories - 1   ▸ Additional crime categories - 2

Balance test result for Robbery

- The rejection of the null hypothesis for the UCR 'Robbery' category implies that neighbourhoods with a higher rate are assigned a higher *'actual expenditure.'*

- To check this, I run a regression:

$$\left(\frac{\textit{actual expenditure}}{\textit{planned expenditure}}\right)_{i,t} = \mu_1 + x_i'\nu + \mu_2 tc_{i,t} + \lambda_j + \lambda_t + \sum_{h=1}^{3} \kappa_h rob_{i,t-h} \tag{2}$$

- I find that UCR 'Robbery' rate in the pretreatment periods are jointly statistically significant with an F-statistic of 4.47 (p-value $= 0.0040$).

- However, when using my definition of 'Street robbery,' I cannot reject the null hypothesis of the parameters being jointly zero with an F-statistic of 1.07 (p-value $= 0.3595$).

- This suggests that the aggregation of crimes matters for the balance test results.

Participatory Budget cameras

Table 4. Selected variables for neighbourhoods that voted for cameras in the PB program

	Value
Unique neighbourhoods that voted for cameras	628
Voted for cameras once	428
Voted for cameras twice	165
Voted for cameras three times or more	35
Cameras as the winning option	867
Positive ‘actual’ expenditure	717
Zero ‘actual’ expenditure	148
Average PB ‘actual’ expenditure	$18,426.87
Standard deviation PB ‘actual’ expenditure	$10,990.40
Average number of cameras	8.49

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Empirical strategy

For implementation, I made the following adjustments:

- I calculate the *PB cameras rate* per 100,000 individuals as follows:

$$PBC_{i,t} = \frac{AE_{i,t}}{4,000} * \frac{100,000}{Pop_i}$$

- I calculate the crime rates per 100,000 and total cameras per 100,000.
- I choose the elasticity of the crime rate to the PB cameras for interpretation purposes, by employing the inverse hyperbolic sine function.[2] Graph
- Thus, any variable $\tilde{z}$ denotes the variable (as rate) transformed with the inverse hyperbolic sine function.

[2] Let $\tilde{z}$ denote any random variable Z which has been transformed using the inverse hyperbolic sine transformation, such that $\tilde{z}$=$archsinh(Z)$=$ln(Z+(Z^2+1)^{1/2})$ (Bellemare and Wichman, 2020).

Empirical strategy

The regression equation is:

$$\tilde{y}_{i,t} = \alpha + \beta_0 \tilde{pbc}_{i,t} + \beta_1 1[Cameras_{i,t}] + \tilde{x}_i' \gamma + \phi \tilde{tc}_t + \lambda_t + \lambda_j + \varepsilon_{i,t} \tag{3}$$

where

- $\tilde{y}_{i,t}$ is the neighbourhood i crime rate in quarter t
- $\tilde{pbc}_{i,t}$ is the PB cameras per 100,000
- $1[Cameras_{i,t}]$ is an indicator variable for choosing cameras
- $\tilde{x}_i$ is a vector of covariates (population, fraction of population aged 15 and older, unemployment rate, fraction of population with access to social security, the fraction of male-headed households)
- $\tilde{tc}_t$ is the total number of cameras per capita,[3]
- λ_j and λ_t are delegation and quarter fixed effects respectively
- $\varepsilon_{i,t}$ is an error term.

[3] This is calculated as the neighbourhood-level number of government cameras and previous years PB cameras divided by the population, and multiplied by 100,000.

FBI's UCR Part I Violent Crimes and Part II Crimes

Table 5. Estimated elasticity of installed cameras per 100, 000 individuals.

	FBI Part I Violent Crimes				
	Criminal homicide	Rape	Robbery	Aggravated assault	Part I Violent Crimes
PB cameras	-0.00566	0.00117	0.0170*	-0.00384	0.0100
	(0.00526)	(0.00631)	(0.00775)	(0.00578)	(0.00747)
Observations	26,276	26,276	26,276	26,276	26,276

	FBI Part II Crimes			
	Vandalism	Disorderly conduct	Drug abuse violations	Part II Crimes
PB cameras	0.00877	0.0124***	-0.000256	0.0156
	(0.00816)	(0.00368)	(0.00737)	(0.00868)
Observations	26,276	26,276	26,276	26,276

Clustered standard errors at the delegation level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions control for the neighbourhood characteristics, delegation fixed effects, quarter fixed effects, an indicator variable for choosing cameras, and quadratic terms for population and the unemployment rate.

FBI's UCR Property crimes

Table 6. FBI Part I Property Crimes - estimated elasticity of installed cameras per 100,000 individuals.

	Larceny-theft	Passersby theft	Theft from auto
PB cameras	0.0119	0.000311	0.0249**
	(0.00704)	(0.00498)	(0.00810)

	Burglary	Motor vehicle theft	Part I Property Crimes
PB cameras	0.00954	-0.00199	0.0150*
	(0.00841)	(0.00760)	(0.00678)
Observations	26,276	26,276	26,276

Clustered standard errors at the delegation level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions control for the neighbourhood characteristics, delegation fixed effects, quarter fixed effects, an indicator variable for choosing cameras, and quadratic terms for population and the unemployment rate.

Additional crimes

Leveraging the granularity of the data, I can check for the *camera deterrence effect* on other crime categories.

Table 7. Estimated elasticity of installed cameras per 100,000 individuals on crime

	Manslaughter	Assault	Street robbery	Car driver robbery	Delivery service theft
PB cameras	-0.00434	-0.000391	0.0210**	0.0150*	0.0101*
	(0.00586)	(0.00732)	(0.00776)	(0.00692)	(0.00414)
Observations	26,276	26,276	26,276	26,276	26,276

Clustered standard errors at the delegation level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions control for the neighbourhood characteristics, delegation fixed effects, quarter fixed effects, an indicator variable for choosing cameras, and quadratic terms for population and the unemployment rate.

Additional crimes

Table 8. Estimated elasticity of installed cameras per 100,000 individuals on crime

	Carjacking	Motor vehicle theft	Theft from auto	Auto parts theft
PB cameras	-0.0106	-0.00191	0.00556	0.00735
	(0.00792)	(0.00528)	(0.00748)	(0.00713)
Observations	26,276	26,276	26,276	26,276

	Business customer robbery	Business robbery	Secure business robbery	Burglary
PB cameras	-0.00341	0.00189	0.0164	0.00587
	(0.00543)	(0.00671)	(0.00880)	(0.00746)
Observations	26,276	26,276	26,276	26,276

Clustered standard errors at the delegation level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions control for the neighbourhood characteristics, delegation fixed effects, quarter fixed effects, an indicator variable for choosing cameras, and quadratic terms for population and the unemployment rate.

Discussion

Why is there no evidence to support the *camera deterrence effect*?

a) Amount of resources actually spent is still very small. On average, areas that voted for cameras receive 69% of the planned budget, with a standard deviation of 38.6%.

b) Limited number of operators for camera monitoring: Assuming no increase in the number of 2016 operators (1,800), three eight-hour shifts, with an equal amount of operators each, every operator would have to monitor 29 cameras.[4]

c) The location of the PB cameras is unobserved, which could obscure the effects by spillovers to areas within the same neighbourhood but where no cameras were installed.

[4] The total number of cameras at the end of the period is 17,560 = 13,576 (government cameras) + 3,984 (PB cameras).

Concluding remarks

- First paper that investigates CCTV systems' deterrence effect in Mexico City, particularly in the PB program context, employing a novel dataset.
- I develop an identification strategy for estimating the cameras' deterrence effect in a new environment.
- I find that cameras do not significantly deter crime.
- Future work should employ a different control group, and discuss other identification strategies.

What is happening with certain crimes?

- The estimates for robbery, theft from auto, part I property crimes, and disorderly conduct, and street robbery, car driver robbery and delivery service theft have the opposite sign of what was expected, and are statistically significant.
- My original identifying assumption is potentially not closing the backdoor paths between the neighborhood i's crime rate, $Y_{i,t}$ and the *'actual expenditure'* it receives, $AE_{i,t}$.
- I have not considered here the persistency of the crime rate in the neighborhoods. I introduce a slight modification of the identifying assumption:

$$E[Y_{i,t}|1[Cameras_{i,t}] = 1, X_i, \lambda_t, \lambda_j, TC_t, Y_{i,t-1}] = E[Y_{i,t}|1[Cameras_{i,t}] = 1, X_i, \lambda_t, , \lambda_j, TC_t, Y_{i,t-1}, AE_{i,t}]$$

Estimation with the new CIA

Estimated elasticity of installed cameras per 100, 000 individuals on crime

	FBI Crimes			
	Robbery	Theft from auto	Part I property crimes	Disorderly conduct
Elasticity	0.00716	0.0191*	0.00626	0.0108**
	(0.00745)	(0.00807)	(0.00644)	(0.00376)
Observations	26276	26276	26276	26276

	Additional crimes		
	Street robbery	Car driver robbery	Delivery service theft
Elasticity	0.0112	0.0119	0.00874
	(0.00749)	(0.00696)	(0.00430)
Observations	26276	26276	26276

Clustered standard errors at the delegation level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions control for the neighbourhood characteristics, delegation fixed effects, quarter fixed effects, an indicator variable for choosing cameras, and quadratic terms for population and the unemployment rate.

General categories of the PB program

The general categories for the PB program are the following:

- Services and Construction (e.g. speed bumps, sidewalks, among others).
- Urban equipment (e.g., garbage trucks).
- Urban Infrastructure (e.g., passersby bridges, traffic lights).
- Security-related expenditures (e.g., surveillance cameras, police stations).

Any project can be proposed by any neighbourhood inhabitant within these general categories. Back to PB

Additional crime categories - 1

Table A1. Pretreatment crimes rates - equality of means.

	Mean				
	Whole Sample (1)	Ratio below the median (2)	Ratio above the median (3)	Difference (4)	t-statistic (5)
Manslaughter	6.00e-08	-.6015601	.6376143	-1.239174	-1.8147
	(.3446725)	(.5499441)	(.4048139)	(.682871)	(0.0697)
Assault	7.69e-08	-.1749815	.185469	-.3604505	-0.2050
	(.8914451)	(1.507296)	(.906025)	(1.758642)	(0.8376)
Street robbery	-6.80e-09	-5.911624	6.265933	-12.17756	-2.1573*
	(2.866227)	(4.884769)	(2.829129)	(5.644904)	(0.0311)
Business customer robbery	5.29e-09	.0017621	-.0018677	.0036297	0.0220
	(.0846217)	(.1577297)	(.0494687)	(.1653052)	(0.9825)
Business robbery	6.00e-09	-.4665426	.4945046	-.9610472	-0.5985
	(.8148971)	(1.394986)	(.7951573)	(1.605696)	(0.5496)
Secure business robbery	-1.64e-09	.0239465	-.0253817	.0493283	1.0985
	(.0225855)	(.0345918)	(.0286361)	(.0449068)	(0.2721)

Standard errors in parentheses for columns (1)-(4), p-value for column (5)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Back to pretreatment crimes

Additional crime categories - 2

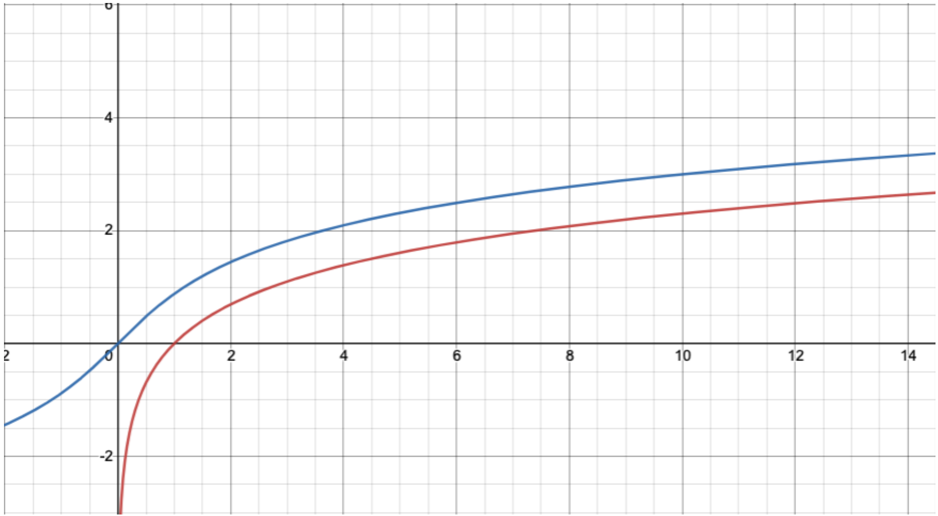
Table A2. Pretreatment crimes rates - equality of means.

	Mean				
	Whole Sample	Ratio below the median	Ratio above the median	Difference	t-statistic
	(1)	(2)	(3)	(4)	(5)
Car driver robbery	2.94e-08	-.3963271	.4200807	-.8164078	-0.6808
	(.6004359)	(.864282)	(.831227)	(1.199134)	(0.4960)
Delivery service theft	-1.69e-08	.0517333	-.0548339	.1065672	0.3144
	(.170984)	(.2731488)	(.200694)	(.3389518)	(0.7532)
Motor vehicle robbery	-6.82e-08	-.9087999	.9632681	-1.872068	-1.0817
	(.8654657)	(1.217577)	(1.229896)	(1.730647)	(0.2795)
Motor vehicle and machinery theft	1.57e-08	-.1105463	.1171719	-.2277182	-0.3912
	(.2894446)	(.3690509)	(.4501176)	(.5820691)	(0.6957)
Theft from auto	-6.73e-08	-1.351863	1.432885	-2.784748	-1.6309
	(.85884899)	(1.311774)	(1.093037)	(1.707478)	(0.1030)
Auto parts theft	6.23e-08	.3223229	-.3416409	.6639638	0.4173
	(.8068751)	(1.370375)	(.8085258)	(1.591113)	(0.6765)

Standard errors in parentheses for columns (1)-(4), p-value for column (5)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

▸ Back to pretreatment crimes



Back to Empirical strategy