# Design of Two-Stage Experiments with an Application to Spillovers in Tax Compliance

Guillermo Cruces
Nottingham & CEDLAS-UNLP

Dario Tortarolo
Nottingham & IFS

Gonzalo Vazquez-Bare UC Santa Barbara

78th IIPF Annual Congress, Linz Austria

August 11, 2022

#### Motivation

- Social interactions among units targeted/non-targeted by policies are common
- This poses challenges for the design and evaluation of RCTs
- Early literature: ex-post analysis of untreated units [e.g., Miguel & Kremer'04]
- Moreover, in public finance, interference/spillovers among tax units is understudied

### Contribution of our paper

- We make two contributions:
  - 1. **Methodological:** develop a framework for Partial Population experiments in samples where units are grouped into mutually exclusive clusters [e.g., Duflo & Saez, 2003]
  - 2. Empirical: large-scale RCT designed to capture spillovers in property tax compliance
- Key: experimental design with built-in spillovers—instead of as an afterthought

### Design of Partial Population Experiments

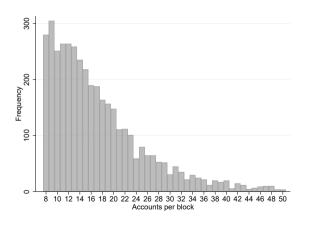
- Goal: estimate within-group spillovers (e.g., employees in firms)
- Partial Population (PP) experiments:
  - Groups randomly divided into different "intensities" (saturations)
  - Units within each group randomly assigned to treatment and control
- Intuition: compare units across groups with different treatment intensities

### Challenges for Designing PP Experiments

- Two-stage design
- Multiple treatments
  - Compare units exposed to different treatment intensities
- Within-group correlations (clustering)
- Heterogeneity in group sizes
  - Group sizes tend to vary widely in practice (e.g., electoral precincts, schools)
  - Literature and software (e.g., Stata's **power**) make restrictive assumptions (e.g., equally-sized groups,  $N_T$  proportional to  $N_C$ ...)

### **Group size heterogeneity is commonplace**

Taxable properties per street-block in Tres de Febrero



#### Two practical implications:

- 1.  $\mathbb{V}[\hat{\beta}]$  needs an adjustment term. Otherwise:
  - ⇒ Power is overestimated
  - ⇒ MDEs underestimated
- 2. Can affect the accuracy of the large sample normal approx
  - ⇒ Power calculations misleading

### **Methodological Contribution**

- We derive an asymptotic variance approximation that allows for:
  - Multiple treatment intensities
  - ► General forms of intracluster correlation and heteroskedasticity
  - Cluster size heterogeneity

### **Methodological Contribution**

- We derive an asymptotic variance approximation that allows for:
  - ► Multiple treatment intensities
  - ▶ General forms of intracluster correlation and heteroskedasticity
  - Cluster size heterogeneity
- ullet These factors affect  $\mathbb{V}[\hat{eta}]...$  but have been overlooked by the literature ullet
  - ▶ Using data from existing studies we show that corrected MDEs can be 20% to 30% larger!

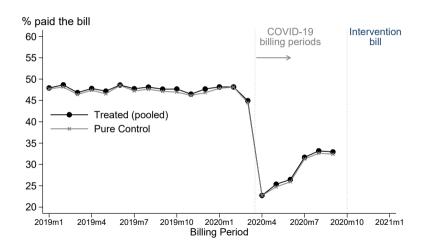
### **Methodological Contribution**

- We derive an asymptotic variance approximation that allows for:
  - ► Multiple treatment intensities
  - ▶ General forms of intracluster correlation and heteroskedasticity
  - Cluster size heterogeneity
- ullet These factors affect  $\mathbb{V}[\hat{eta}]...$  but have been overlooked by the literature ullet
  - ▶ Using data from existing studies we show that corrected MDEs can be 20% to 30% larger!
- Our formula nests other cases [e.g., Duflo et al, 2007; Hirano & Hahn, 2010; Baird et al, 2018] and can be applied in a wide range of designs (e.g., PP, clustered, stratified...)

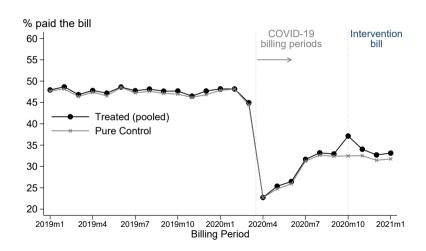
### **Spillovers in Property Tax Compliance**

- Ample evidence on direct effects of tax compliance interventions [Antinyan & Asatryan'19]
- We know little about interference among tax units
- We teamed up with a large municipality in Argentina (Tres de Febrero) Neighbors must pay a monthly bill on their real estate ( $\sim$ 70k units)
- Context: arrears mainly due to COVID-19 lockdown
  - $\Rightarrow$  we devised an intervention in Oct'2020, when mobility restrictions started to ease

# Timely payments of **treated** units increased due to our intervention What about untreated neighbors in treated blocks?



# Timely payments of **treated** units increased due to our intervention What about untreated neighbors in treated blocks?



### What exactly did we do?

- We sent  $\sim$ 25,000 personalized letters to randomly selected accounts with information about the Oct'20 bill, due dates, past due debt, and payment methods
- Critically, we designed the experiment using our framework to maximize the chance of capturing spillover effects



### Design and example of the letter

IOCALIDAD: 11 de Septiembre



DIRECCIÓN: CAR MADARIAGA Nº

C D : 1657

PARTIDA: XXXXXXX/7

Tis queemos contor que chara en Ties de Petrero tu boleta municipal de la Toso por Servicios Generoles (TSG) es 100% digita C i ses, que no se usa más el papel. Prode cocador e elle qui poporto desde el celulor o la composiboria. De sesio manera, no alcolamos entre todo de indebica de cubido di proteiro cudarona el medio ambiente. Se indebido intereste a cumidado de la cultar de subscioció alfet que aposiboria como el el cultar de cubido de la cultar de cultar de cultar de la cultar de cultar de como el cultar de la cultar de cult



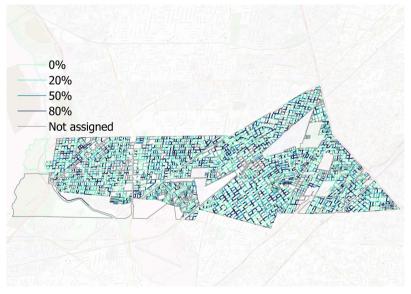
#### Randomization in 2 stages:

- 1) Randomly divide 3,982 street-blocks into 4 categories with ≠ treatment intensity:
  - $T_g = 0$ : pure controls
  - $T_g=1$ : blocks with  ${f 20\%}$  of properties treated
  - $T_g = 2$ : blocks with **50%** of properties treated
  - $T_g = 3$ : blocks with **80%** of properties treated
- Within treated street-blocks, randomly assign accounts to treated (letter) or untreated

▶ KITCHEN: Treatment Assignment, Power, MDE

Muchas gradas! 10/17

# Map of the municipality & the experimental design



### **Empirical strategy**

• In multi-treatment experiments, effects on outcome  $Y_{ig}$  are commonly estimated through saturated OLS regressions:

$$Y_{ig} = \alpha + \sum_{t=1}^{3} \beta_{0t} \mathbb{1}(T_g = t)(1 - D_{ig}) + \sum_{t=1}^{3} \beta_{1t} \mathbb{1}(T_g = t)D_{ig} + \varepsilon_{ig}$$

where

$$\beta_{0t} = \mathbb{E}[Y_{ig}|D_{ig} = 0, T_g = t] - \mathbb{E}[Y_{ig}|D_{ig} = 0, T_g = 0]$$

Spillover effects on untreated units

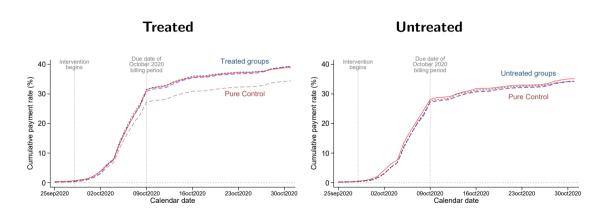
and

$$\beta_{1t} = \mathbb{E}[Y_{ig}|D_{ig} = 1, T_g = t] - \mathbb{E}[Y_{ig}|D_{ig} = 0, T_g = 0]$$

Total effects on treated units

• We allow  $\varepsilon_{ig}$  to be correlated within blocks and use a cluster-robust variance estimator

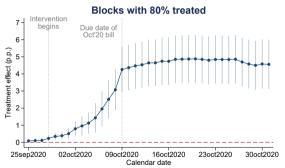


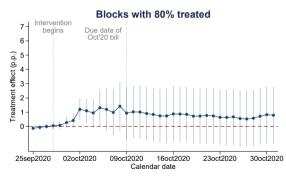


# Daily payment rates of the Oct'2020 bill Blocks with 80% treated



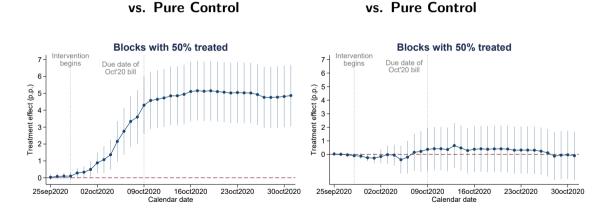
Untreated vs. Pure Control





# Daily payment rates of the Oct'2020 bill Blocks with 50% treated

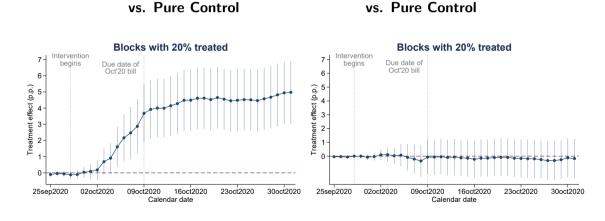
Treated



Untreated

# Daily payment rates of the Oct'2020 bill Blocks with 20% treated

Treated

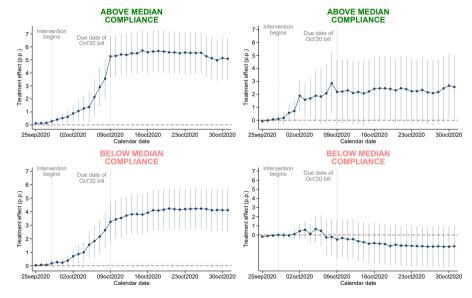


Untreated

### Total and spillover effects for bill payments Placebo Figs Table het

Dependent variable:	Placebo bill:	Intervention bill:		
Pr(pay the bill)	Sep'20	Early	By Oct 31	
	(1)	(2)	(3)	
A. Blocks with 80% treated				
Treated	0.12	0.96***	4.55***	
	(0.69)	(0.28)	(0.74)	
Untreated	-0.30	1.10**	0.79	
	(0.95)	(0.43)	(1.01)	
B. Blocks with 50% treated				
Treated	0.76	1.07***	4.87***	
	(0.88)	(0.41)	(0.93)	
Untreated	0.26	-0.02	-0.10	
	(0.88)	(0.34)	(0.91)	
C. Blocks with 20% treated				
Treated	0.85	0.69*	4.97***	
	(0.93)	(0.42)	(0.99)	
Untreated	0.07	0.11	-0.18	
	(0.68)	(0.26)	(0.72)	
Payment Rate of Pure Control	29.70	5.15	34.37	
Observations	68,806	68,806	68,806	
Number of clusters (blocks)	3,981	3,981	3,981	

### Above/Below 2019 compliance - Blocks 80% Distribution



#### **Conclusions**

- General framework to conduct experiments to estimate spillovers
  - ▶ Allows for group size heterogeneity, heteroskedasticity, ICC, ...
  - Derive optimal choice of group-level probabilities
- Application to property tax compliance in Argentina
  - Our letters increased payment rates of both treated and untreated neighbors
  - ▶ **Direct effects:** 4.5 p.p. (16% of the payment rate in pure control blocks)
  - ➤ **Spillover effects:** more modest in magnitude, precisely estimated Larger in "good payer" blocks with 80% treated

Thank you!

Dario Tortarolo

### Setup • Back

- Groups  $g = 1, \ldots, G$  with units  $i = 1, \ldots, n_g$
- Total sample size  $n = \sum_{g} n_{g}$
- Multi-valued unit-level treatment  $A_{ig} = \{a_0, a_1, a_2, \dots, a_K\}$
- Assignment probabilities:

$$\pi_g(a_k) = \mathbb{P}_g[A_{ig} = a_k], \quad \pi_g(a_k, a_l) = \mathbb{P}_g[A_{ig} = a_k, A_{jg} = a_l]$$

Moments:

$$\sigma^{2}(a_{k}) = \mathbb{V}[Y_{ig}|A_{ig} = a_{k}]$$

$$\rho(a_{k}, a_{l}) = cor(Y_{ig}, Y_{jg}|A_{ig} = a_{k}, A_{jg} = a_{l})$$

### Setup • Back

Empirical strategy: estimate

$$Y_{ig} = \alpha + \sum_{k=1}^{K} \beta_k \mathbb{1}(A_{ig} = a_k) + \varepsilon_{ig}$$

by OLS, where

$$\beta_k = \mathbb{E}[Y_{ig}|A_{ig} = a_k] - \mathbb{E}[Y_{ig}|A_{ig} = a_0]$$

and

$$\hat{\beta}_k = \bar{Y}_k - \bar{Y}_0$$

• Error terms correlated within groups

### Main Result • Back

### Asymptotic Approximation

Under regularity conditions, if

$$\max_{g \leq G} \frac{n_g^2}{n} \to 0, \quad \frac{\sum_{g=1}^G n_g^4}{n^2} \leq C < \infty,$$

then  $\hat{\beta}_k \stackrel{a}{\sim} \mathcal{N}(\beta_k, V_k)$  where:

$$egin{aligned} V_k &= rac{\sigma^2(\mathsf{a}_k)}{\sum_{g} n_g \pi_g(\mathsf{a}_k)} \left\{ 1 + 
ho(\mathsf{a}_k, \mathsf{a}_k) rac{\sum_{g} n_g (n_g - 1) \pi_g(\mathsf{a}_k, \mathsf{a}_k)}{\sum_{g} n_g \pi_g(\mathsf{a}_k)} 
ight\} \ &+ rac{\sigma^2(\mathsf{a}_0)}{\sum_{g} n_g \pi_g(\mathsf{a}_0)} \left\{ 1 + 
ho(\mathsf{a}_0, \mathsf{a}_0) rac{\sum_{g} n_g (n_g - 1) \pi_g(\mathsf{a}_0, \mathsf{a}_0)}{\sum_{g} n_g \pi_g(\mathsf{a}_0)} 
ight\} \ &- 2\sigma(\mathsf{a}_k)\sigma(\mathsf{a}_0)
ho(\mathsf{a}_k, \mathsf{a}_0) rac{\sum_{g} n_g (n_g - 1) \pi_g(\mathsf{a}_k, \mathsf{a}_0)}{\sum_{g} n_g \pi_g(\mathsf{a}_k) \sum_{g} n_g \pi_g(\mathsf{a}_0)} \end{aligned}$$

### Main Result: Intuition • Back

• The formula is an explicit version of

$$\mathbb{V}[\bar{Y}_k - \bar{Y}_0] = \mathbb{V}[\bar{Y}_k] + \mathbb{V}[\bar{Y}_0] - 2\mathbb{C}\mathsf{ov}(\bar{Y}_k, \bar{Y}_0)$$

allowing for:

- ► Intracluster correlation
- Heteroskedasticity
- Unequal probabilities between groups
- Group size heterogeneity

### Main Result: Intuition • Back

• Condition:

$$\max_{g \le G} \frac{n_g^2}{n} \to 0$$

restricts the relative size of the largest group

- ► Ensures that no group "dominates" the sample
- Condition:

$$\frac{\sum_{g=1}^G n_g^4}{n^2} \le C < \infty$$

bounds the fourth moment of the distribution

► Rules out fat tails (outliers)

# Why is group size heterogeneity important? • Back

• It affects the variance of estimators

$$\mathbb{V}[\hat{\beta}] \approx \sigma^2[1 + \rho(ICC, \bar{n}, Var(n_g))]$$

- ▶ Ignoring  $Var(n_g)$  underestimates  $\mathbb{V}[\hat{\beta}]$   $\Rightarrow$  overestimates power
- It affects inference and power calculations
  - Normal approx may be inaccurate if groups are "too heterogeneous"
  - ► Carter et al (2017), Djogbenou et al (2019), Hansen and Lee (2019)

## Illustration using data from four published studies • Back

- Ichino & Schundeln (2012), Haushofer & Shapiro (2016), Gine & Mansuri (2018) and Imai, Jiang & Malani (2021)
- ullet In common: clusters randomly assigned to eq treatment intensities to estimate spillovers
- We calculate standard errors and MDEs accounting for cluster size heterogeneity using the median values of number of groups, G=95, average group size,  $\bar{n}=23.3$ , and group size SD,  $sd(n_g)=15.2$ .
- We compare "adjusted" standard errors and MDEs with "undajusted" ones—those obtained if (incorrectly) ignoring cluster size heterogeneity.

Gi

Ichino and Schündeln (2012)

Mean

Median

Imai, Jiang and Malani (2021)

Giné and Mansuri (2018)
Haushofer and Shapiro (2016)

Table A4: Sample sizes in existing literature

Sample size

2,736

1.440

10,030

3.769

2,088

868

No. of groups

67

123

39

95

434

165.8

Ave. group size

39.4

23.4

22.3

23.1

27.05

23.3

Sd. group size

16.7

14.8

9.6

15.5

14.2

15.2

-	Adj.	Unadj.	Ratio	
$\rho = 0.1$				

0.1768

0.0569

0.2593

0.2098

0.3437

0.1136

0.3252

0.2622

0.4284

0.1420

IS

IJM

 $\rho = 0.5$  GM

HS

IS

IJM

 $\rho = 0.8$  GM

HS

IS

IJΜ

$\rho = 0.1$				
GM	0.1262	0.1181	1.0687	0.3536
$_{\mathrm{HS}}$	0.1053	0.0932	1.1307	0.2951

0.1667

0.0497

0.2393

0.1783

0.3171

0.0950

0.2997

0.2218

0.3941

0.1181

Standard error

Table A5: Numerical results

1.0608

1.1453

1.0835

1.1761

1.0840

1.1961

1.0851

1.1818

1.0869

1.2024

 $\overline{\text{MDE}}$ 

Unadj.

0.3308

0.2610

0.4670

0.1393

0.6705

0.4997

0.8884

0.2661

0.8397

0.6215

1.1042

0.3309

Ratio

1.0689

1.1307

1.0608

1.1450

1.0835

1.1761

1.0840

1.1962

1.0851

1.1818

1.0869

1.2025

Adj.

0.4954

0.1595

0.7265

0.5877

0.9630

0.3183

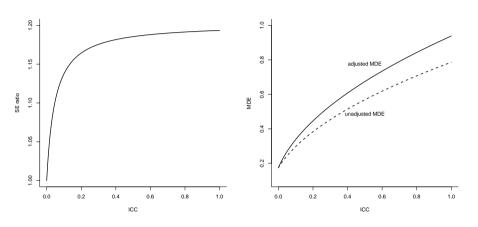
0.9112

0.7345

1.2002

0.3979

Figure: Adjusted and unadjusted standard errors and MDEs • Back



#### (a) Ratio of adjusted to unadjusted SEs

(b) MDE

**Notes**: Adjusted magnitudes account for group size variability. Unadjusted magnitudes assume no group size variability, i.e. zero variance of group size.

### PP Experiment: Design • Back

- We randomly divide city street-blocks into four categories:
  - $ightharpoonup T_g = 0$ : pure controls with prob  $q_0$
  - $ightharpoonup T_g=1$ : blocks with 20% of properties treated with prob  $q_1$
  - $ightharpoonup T_g=2$ : blocks with 50% of properties treated with prob  $q_2$
  - $ightharpoonup T_g = 3$ : blocks with 80% of properties treated with prob  $q_3$
- Goal: choose  $q_t = \mathbb{P}[T_g = t]$ , t = 0, 1, 2, 3
- ullet We set up a system of eqs to incorporate constraints on  $\{q_t\}_t$

# Constrained choice of $\{q_t\}_t$ ullet Back

- Choose  $q_1, q_2, q_3$ , with  $q_0 = 1 q_1 q_2 q_3$
- ullet Total sample size  $n=\sum_{oldsymbol{g}} n_{oldsymbol{g}}$
- The total number of letters sent (L) should equal the expected number of treated:

$$L = n(0.2q_1 + 0.5q_2 + 0.8q_3)$$

- ullet Categories  $T_g=1$  and  $T_g=3$  are symmetric, so  $q_1=q_3$
- This leaves two probabilities to be determined:  $q_2$  and  $q_3$
- Idea: balance variances across assignments

## Constrained choice of $\{q_t\}_t$ ullet Back

- ullet The "hardest" effects (smallest cells) to estimate are  $heta_3$  and  $au_1$ 
  - ▶ Spillover effect in 80% groups and direct effect in 20% groups
- We choose  $q_2$  and  $q_3$  by setting:

$$V(\hat{\theta}_3) = V(\hat{\theta}_2)$$

based on our variance approximation

• We assume  $\sigma^2(0,2) pprox \sigma^2(0,3) = \sigma^2$  and ho pprox 0.1

## Power calculations • Back

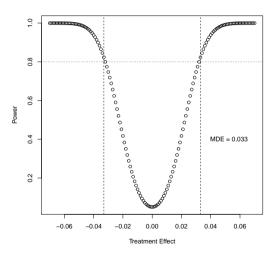
#### **Probabilities:**

	Prob
$\overline{q_0}$	0.273
$q_1$	0.302
$q_2$	0.121
<b>q</b> 3	0.302

#### **Expected sample sizes:**

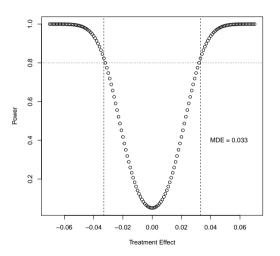
	Blocks	Control Obs	Treated Obs
$T_g = 0$	1,087	18,870	0
$T_g=1$	1,205	16,530	4, 236
$T_g=2$	483	4, 192	4, 184
$T_{g} = 3$	1,205	4,024	16,772
Total	3,980	43,616	25, 192

## Power functions and MDE Back



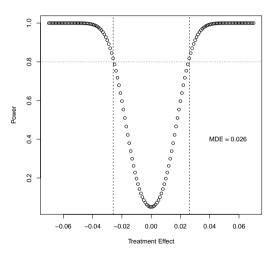
Power function for (d, t) = (0, 3) and (d, t) = (1, 1)

## Power functions and MDE Back



Power function for (d, t) = (0, 2) and (d, t) = (1, 2)

## Power functions and MDE Back



Power function for (d, t) = (1, 3) and (d, t) = (0, 1)

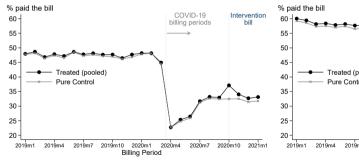
## Balance

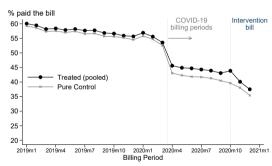
	Property	Front	House	Tenant	Tenant	Bill	N Bills	Digital
	Value	Metres	type	Male	Age	amount	paid 2019	payment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Blocks with 80	% treated:							
Treated	0.01	-8.27	-0.00	-0.00	-0.14	2.81	0.05	-0.00
	(0.02)	(17.77)	(0.00)	(0.01)	(0.40)	(7.81)	(0.09)	(0.01)
Untreated	0.00	-1.76	0.00	0.00	-0.53	6.27	-0.06	-0.00
	(0.02)	(20.70)	(0.01)	(0.01)	(0.53)	(12.95)	(0.12)	(0.01)
B. Blocks with 50	% treated:							
Treated	0.01	12.65	-0.00	-0.00	-0.47	1.16	0.03	0.00
	(0.02)	(20.38)	(0.01)	(0.01)	(0.50)	(9.21)	(0.11)	(0.01)
Untreated	0.01	25.30	-0.00	-0.00	-0.42	1.88	0.02	0.01
	(0.02)	(20.66)	(0.01)	(0.01)	(0.48)	(9.66)	(0.11)	(0.01)
C. Blocks with 20	% treated:							
Treated	0.02	32.57*	-0.01	0.01	0.10	5.94	0.07	-0.01
	(0.02)	(16.79)	(0.01)	(0.01)	(0.54)	(9.55)	(0.12)	(0.01)
Untreated	0.02	19.14	-0.01	-0.01	0.12	1.32	0.00	0.00
	(0.02)	(14.05)	(0.00)	(0.01)	(0.40)	(7.77)	(0.09)	(0.01)
Mean Pure Control	13.64	841.50	0.91	0.62	19.15	368.66	6.71	0.35
Observations	64,932	68,808	68,808	46,419	52,714	68,808	68,808	38,112
Number of clusters	3,979	3,981	3,981	3,973	3,976	3,981	3,981	3,968

## Direct effect on treated neighbors

Timely payments (left) and w/past-due payments (right)

#### (a) Payment rates in levels

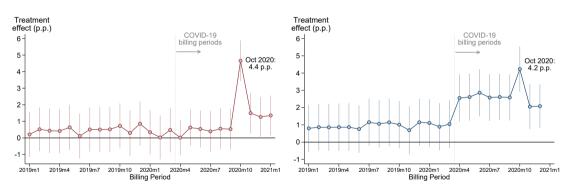




## Direct effect on treated neighbors

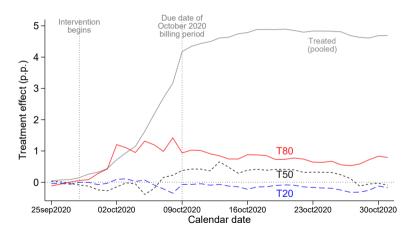
Timely payments (left) and w/past-due payments (right)

#### (b) Difference relative to pure control group



## Payment rate of the Oct'2020 bill • Back

Figure: Difference relative to pure control group



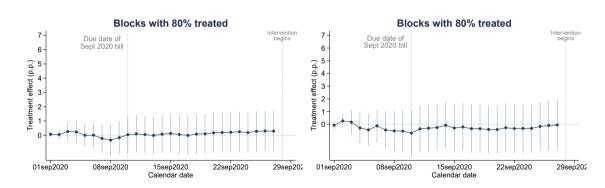
## Daily payment rates of the **Sep'2020** bill

[PLACEBO]

Blocks with 80% treated → Back

Treated vs. Pure Control

Untreated vs. Pure Control



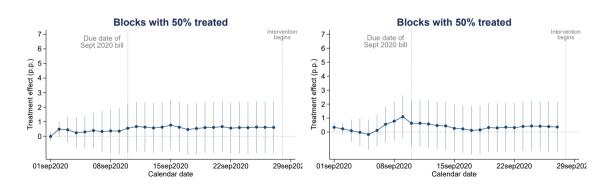
## Daily payment rates of the **Sep'2020** bill

[PLACEBO]

Blocks with 50% treated → Back

Treated vs. Pure Control

Untreated vs. Pure Control



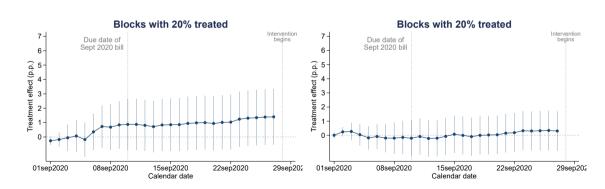
# Daily payment rates of the Sep'2020 bill

[PLACEBO]

Blocks with 20% treated → Back

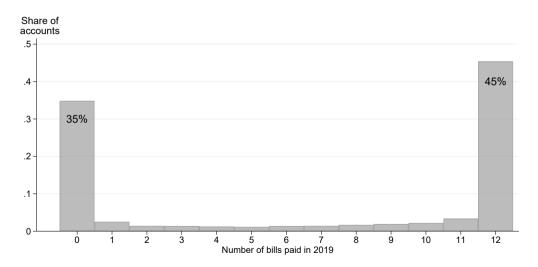
# Treated vs. Pure Control

# Untreated vs. Pure Control



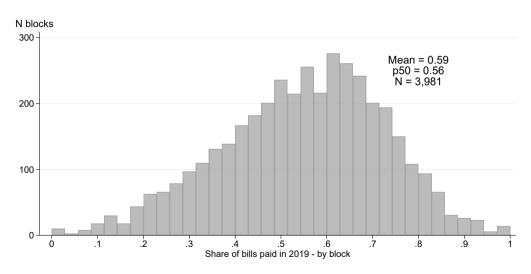
## Tax compliance in 2019: always payers and never payers

Stylized fact in property taxation • Back



## Tax compliance in 2019: always payers and never payers

Stylized fact in property taxation • Back



## Heterogeneous Effects (pre-registered!) • Back



	Placebo bill: Sep'20		Intervention bill:				
			Early		By Oct 31		
	Below	Above	Below	Above	Below	Above	
	Median	Median	Median	Median	Median	Median	
	(1)	(2)	(3)	(4)	(5)	(6)	
A. Blocks with 80% treated							
Treated	0.10	0.28	0.86**	1.06**	4.12***	5.09***	
	(0.73)	(0.81)	(0.34)	(0.42)	(0.79)	(0.81)	
Untreated	-1.55	0.78	0.55	1.58**	-1.25	2.56**	
	(1.09)	(1.24)	(0.50)	(0.67)	(1.16)	(1.27)	
B. Blocks with 50% treated							
Treated	1.54	0.69	1.24**	1.02	4.81***	5.67***	
	(0.99)	(1.12)	(0.50)	(0.62)	(1.07)	(1.08)	
Untreated	0.81	0.36	0.10	-0.03	1.34	-0.76	
	(0.94)	(1.15)	(0.43)	(0.50)	(1.00)	(1.14)	
C. Blocks with 20% treated							
Treated	1.32	0.27	0.85*	0.52	5.41***	4.40***	
	(1.11)	(1.24)	(0.52)	(0.63)	(1.21)	(1.27)	
Untreated	0.27	-0.32	0.68**	-0.42	0.61	-1.09	
	(0.72)	(0.80)	(0.33)	(0.38)	(0.77)	(0.82)	
Payment Rate of Pure Control	20.05	38.19	3.63	6.49	23.53	43.91	
Observations	32,361	36,445	32,361	36,445	32,361	36,445	
Number of clusters (blocks)	2,013	1,968	2,013	1,968	2,013	1,968	