

## CHAPTER 0: Pinotti (2020), "The Credibility Revolution in the Empirical Analysis of Crime," Sections 1–3

### 1. Main challenges:

A. **Measurement error:** can be extremely severe, eg. correl GDP-Homicide rel is neg, GDP-sex assaults is pos

a. Causes:

- First, debate and discretion on the very **definition** of many important concepts in social sciences I (e.g., “social capital”).
- **Small samples**
- **Crime data mismeasurement** is different, and is **often non-random**: endogenous reporting of crime: reporting depends on factors like victims' willingness or law enforcement behavior. This leads to a systematic underestimation of true crime rates, and the degree of underreporting can vary with:
  - o How widespread crime is
  - o Enforcement intensity
  - o Social norms/values
  - o etc

Example: Reporting of sexual assaults depends on societal attitudes; Nordic countries show high reported rates due to greater willingness to report.

\* *Classical measurement error (random, uncorrelated with outcome or regressors) causes attenuation bias: estimates are biased toward zero. Intuition: When an independent variable is measured imprecisely, its correlation with the dependent variable weakens, reducing the estimated effect.*

b. Possible solutions:

- **Limit the analysis** to crimes that are less subject to underreporting. For example, the definition of **homicide** does not vary across countries and the extent of underreporting is negligible. Indeed, differently from the evidence on sexual assaults – homicide rates are negatively correlated with country GDP. Makes sense
- Second, impose **restrictions on the structure of measurement error** and difference it away in the econometric specification: If one is willing to assume that (i) reported crimes are proportional to actual crimes and (ii) the constant of proportionality is the product of region-specific and year-specific components, THEN a log-linear specification with time and area dummies would absorb measurement error into region and year fixed effects (see appendix for details).
- Third solution: Even if criminals hide actions, they often leave a “**statistical trace**” in data (ex. evidence: match-rigging in Sumo, tariff evasion etc). Sometimes by looking at the entire distribution of the data it is possible to detect statistical anomalies that are not observable in individual-level data. More in the Appendix\*2
- Fourth, **Triangularize** the data: gain insights from multiple measures

### B. The issue of causality

a. Issues:

- **Reverse Causality:** more crime more police! (you have DIA exactly because there is mafia).
- **OVB:** cities with higher police presence are likely to differ also along other characteristics (ex. socio economic conditions). 1) use controls, 2) could be possible to sign OVB
- **RCTs are unfeasible:** 1) **ethical constraints**, 2) **practical constraints** (to see the effect of mafia... parachute mafia bosses?).

b. Recent advancements:

- The combination of detailed micro data and
- Quasi-experimental methods (e.g., DiD, RD, IV) has improved the credibility of causal estimates (eg indulto)

### 2. Organized crime and corruption

a. Issues: It is **harder to study** organized crime and corruption, despite their larger societal costs.

1. In many countries, **Membership is not legally defined** in the legislative system (Italy: since 1982, 416-bis).
2. **Underreporting is severe due to fear of retaliation, especially where such organizations are more powerful;** Ex. see *surveys of Italian entrepreneurs*.
3. **Tragedy of the commons (victimless crime):** benefits are concentrated, costs are diffuse, victims lack incentives to report or pursue complex, costly legal cases.
4. Identification is hard because such phenomena are **deeply intertwined to pre-existing social factors** (e.g., Sicily).

b. Solutions: **Again, leverage Natural experiments:** Effects of asset seizures **and** government dismissals offer valuable insights.

### APPENDIX

Reported crimes  $R_{it}$  are proportional to true crimes  $C_{it}$ :

$$R_{it} = \theta_{it} \cdot C_{it}$$

The proportionality factor  $\theta_{it}$  is separable into a region-specific and a time-specific component:

$$\theta_{it} = \alpha_i \cdot \delta_t$$

Taking logs of both sides:



$$\log R_{it} = \log C_{it} + \log \alpha_i + \log \delta_t$$

Then the model becomes:

$$\log R_{it} = \log C_{it} + \mu_i + \lambda_t$$

\*2 In deep: Statistical clues to uncover illegal behavior

*Example 1: Duggan & Levitt (2001), Winning Isn't Everything: Corruption in Sumo Wrestling'*

Setting: In sumo tournaments, wrestlers fight 15 matches. Achieving 8+ wins brings large ranking/payoff increases, while 7 or fewer wins yield little gain.

Incentive: A wrestler with 7 wins has a strong incentive to win the 8th. Their opponent with <7 wins—has less to gain.

Evidence: The distribution of wins shows an unusual spike at 8 wins compared to a binomial (random) benchmark.

Conclusion: The data suggests systematic match-fixing.

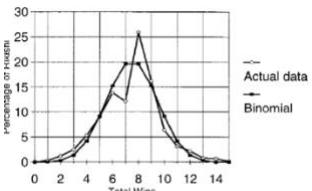


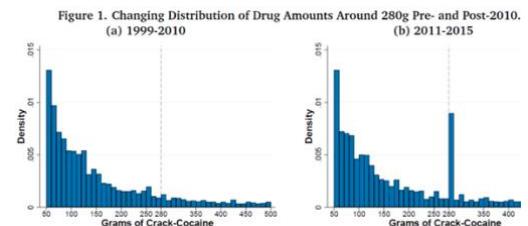
FIGURE 2. WINS IN A SUMO TOURNAMENT

*Example 2: Tuttle (2019) Racial Disparities in Federal Sentencing: Evidence from Drug Mandatory Minimums*

- Until 2010 in the US there was a 10-year mandatory arrest for those trafficking crack-cocaine.

- In 2010, there was a reform of the law to distinguish users from traffickers: the 10-year mandatory minimum threshold for trafficking crack-cocaine increased from 50g to 280g.

- There is a spike at 280g post-2010. Why? Police were manipulating the evidence to ensure people would get at least 10 years of jail.



#### Anastasia Roncada: statistical anomalies

1. *Benford's Law: a Forensic Analysis of Macroeconomic Data Integrity Evaluating Economic Data Through Mathematical Analysis*; Keio University.

Definition: Benford's Law describes a predictable pattern in the frequency of leading digits in naturally occurring datasets: 1 appears ~30% of the time; larger digits (e.g., 9) appear <5%. Small digits dominate because many real-world processes grow multiplicatively.

COMPONENT	SUMMARY
RESEARCH QUESTION	1. Does macroeconomic data (e.g., debt statistics by World Bank) comply with Benford's Law (BL)? = are leading digits distributed according to the Benford pattern? 2. What institutional factors explain deviations (i.e., which governments are likely manipulating data)?
CONTEXT & SETTING	Examines World Debt Statistics (World Bank) for 20 countries (2010–2020).
METHODOLOGY	- Compares digit distributions of debt/financial flows with theoretical BL expectations. - Tests association of BL deviations with institutional quality indicators (Regulatory Quality, Rule of Law, Govt Effectiveness; World Bank WGI).
EMPIRICAL MODEL	<b>Benford Tests:</b> $\chi^2$ goodness-of-fit, Mean Absolute Deviation (MAD) between observed and theoretical distributions.
KEY FINDINGS	- Significant BL deviations in debt statistics, signaling potential manipulation. - Strong correlation: higher Rule of Law, Govt Effectiveness, and Regulatory Quality ↓ deviations (better data integrity).

2. *Detecting Trade Anomalies and Sanctions Evasion in Common High-Priority Items: A Benford's Law Analysis of Triangular Trade Patterns*; Bocconi University

RESEARCH QUESTION	Can we detect sanction circumvention through Benford's Law? Can we find preventive factors that are correlated with sanction circumvention?
DATA	CHPI: Sanctioned high-priority items. Counterfactual: Non-sanctioned, heterogeneous items.
METHODOLOGY	1. Benford's Law is applied to trade statistics to detect anomalies, particularly in sanctioned goods. 2. What factors predict sanction circumvention by neighboring countries? Factors analysed: - Border contiguity with Russia - Corruption. - Political alignment (UN voting for Russia)

#### CHAPTER 1: History and Becker

# 1 Historic Analysis on the Study of Crime

- (1) Aristotle: *Poverty is the mother of crime.*
- (2) Beccaria / Enlightenment: Explain crime as a rational phenomenon.
- (3) Quetelet / Social Physics: Modeled crime like other phenomena in physics, using observational data. He measured who commits crimes and found a relationship between the probability of committing crime and age (peak at 20, male).
- (4) Raffaele Garofalo (1885): First to mention *criminology* as a discipline to understand why people commit crimes. Aim: define what the state can do.
- (5) Cesare Lombroso:
  - (a) Focus on physiological factors (e.g., physiognomy—shape of the face—and crime).
  - (b) Positivist school: focus on describing how people behave (not how they should behave).
  - (c) Scientific approach with empirical evidence.
- (6) Enrico Ferri: Continued Lombroso's work but focused on socioeconomic factors (income, education, neighborhood).
- (7) Rational Choice and Crime:
  - Jeremy Bentham in *Principles in Penal Law*: "The profit of the crime is the force which urges man to delinquency; the pain of the punishment is the force employed to restrain him from it." Idea: individuals compare expected benefits and costs of illegal behavior.
  - Gary Becker, *Crime and Punishment: An Economic Approach*: Models crime as an economic phenomenon. Criminal behavior is analyzed through the lens of rational choice. Criminals make decisions to maximize their utility, like consumers. Each us may commit a crime if the expected benefits from crime exceed expected costs (monetary, social, psychological). Thus, there is no sharp boundary between criminals and non-criminals—just a continuum of individuals with different costs and benefits.

## 1.1 The Decision to Commit a Crime

Individuals commit crime if and only if:

$$(1 - p) \cdot \pi > p \cdot J + w$$

Where:

- $\pi$ : Payoffs from crime
- $J$ : Cost of being punished (fine or jail)
- $p$ : Probability of being arrested
- $w$ : Legitimate earnings (e.g., wage from legal work)

Expected payoff:  $(1 - p) \cdot \pi$

Expected cost:

- Direct cost:  $p \cdot J$
- Opportunity cost:  $w$ , the income missed by committing a crime (among others, one of the reasons why more educated individuals commit less crimes)

## 1.2 Predictions from the Economic Model of Crime

- Deterrence effect: As the probability of arrest ( $p$ ) increases, crime decreases.
- Incapacitation effect: Incarceration mechanically prevents crime while the individual is imprisoned.
- Punishment severity effect: As  $J$  increases, crime decreases (expected cost rises).
- Payoff effect: As  $\pi$  increases, crime increases (expected benefits rise).
- Legitimate earnings effect: As  $w$  increases, crime decreases (opportunity cost rises).

## 1.3 One can now think about

- Effect of an increase in poverty
- Effect of an increase in inequality
- Effect of increased police patrolling
- Effect of longer prison sentences
- Effect of the death penalty

\*1. Remark: Never control for a mediating factor

Example: estimate the effects of police on crime keeping constant the n\_arrests! The effect of policy goes precisely through an increase in arrests! If you include arrest in the regression as a control, you are considering arrest as a constant and, as such, when measuring the effect of police on crime, such an effect will be obviously zero because you are interrupting the causal effect.



## CHAPTER 2: Experiments and the potential outcome model (RCTs)

To solve the challenges of empirical estimation, we often resort to RCTs.

### A. Why empirical estimation in absence of RCTs can be challenging.

**Research question:** Imagine we wish to study crime in Chicago (map). More police stations --> which effect on crime?

**Ideal Experiment:** Whole technical discussion skipped, refer to micro-econometrics. In short: The ideal experiment we would like to run would be to observe different states of the world to compare outcomes with and without police stations for EACH district. In practice, we cannot do that and we are just going to observe one state of the world for each district = we do not have the counterfactual (missing data problem, you are essentially losing 50% of observations).

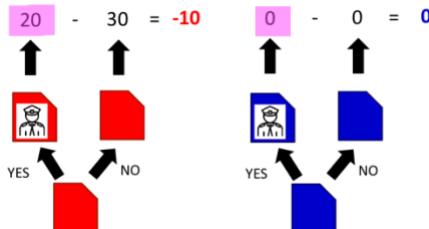
- You see a treated district with outcome 20 homicides
- You see an untreated district with outcome 0 homicides
- A naïve comparison of means would lead you to say that the treated district would have +20 homicides

The problem is that the untreated district could be (are) intrinsically different than the treated one!

⇒ The naïve comparison is determined by selection bias!

$$\mathbb{E}[Y|T=1] - \mathbb{E}[Y|T=0] = \underbrace{\mathbb{E}[Y(1)|T=1] - \mathbb{E}[Y(0)|T=1]}_{ATT} + \underbrace{\mathbb{E}[Y(0)|T=1] - \mathbb{E}[Y(0)|T=0]}_{Selection\ Bias} = -10 + 30 = 20$$

Ex (clearly you cannot observe the outcomes in purple.)



### B. How RCTs solve Selection Bias

Selection bias is always present when studying social phenomena, since the latter are made by people who naturally choose based on what they reckon best for them. So, what is the solution?

- You prevent people from choosing: you **randomly** assign people to the T and the C group. Eliminate the possibility of *a priori* differences in potential outcomes (better if n large)
- Administer a 'treatment'
- Compare outcomes of interest between the T and the C

Ex. So now you have two balanced samples: T and C. The T sample has 5 Red districts with outcome 20 and 5 blue districts with outcome 0. The C sample has 5 Red with outcome 30 and 5 blue with outcome 0. So the average for the treated is 10 while for the non-treated is 15 => ATT = -5, ATT = -10. The counterfactual for the treated group is -30! ATT is an average of the effect on the treated and the effect on the control (ATNC).

#### 2.1 Discussion: Noncompliance with Treatment Assignment!

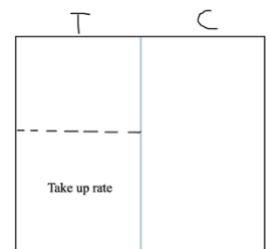
##### **A. Issue:**

- Sometimes people do NOT comply with treatment Assignment (Z)! Some treated may not take up the treatment, some controls may manage to get the treatment! So that Treatment uptake (T) will differ from treatment assignment (Z)
  - Never takers (NT) will never take up the treatment regardless of the assignment
  - Always takers (AT) will always take up the treatment regardless of the assignment

##### **B. Solution**

I. The treatment assignment (being offered a program) is a valid instrument for the actual treatment take up if:

- Independence: Z is randomly assigned.
- Relevance: Z affects T (non-zero first stage), this variation is the one of compliers!
- Exclusion: Z affects Y only via T



- Monotonicity: no defiers

Note that treatment assignment only changes the outcomes of compliers: captures the variation of being assigned to the treatment (AT and NT are irresponsive to treatment). Then clearly if those more likely to take up treatment are those with highest gains we are in trouble.

II. Then, the first stage (reduced form) will be (effect of Z on T):  $E(Y_i|Z_i = 1) - E(Y_i|Z_i = 0)$

This is called intention to treat (ITT) and could be interesting: you cannot force people to enter your program, so you want actually to estimate the effect of just having offered them the treatment. This step requires only the independence assumption.

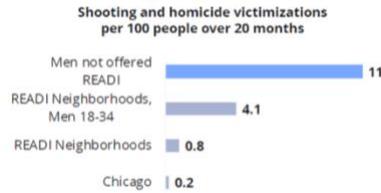
III. What if we want the ATT? In this you want the effect of T on Y

$$\frac{\text{Effect of } Z \text{ on } Y}{\text{reduced form effect}} = \frac{\text{Effect of } Z \text{ on } T}{\text{first stage}} \times \frac{\text{Effect of } T \text{ on } Y}{\text{second stage}} \rightarrow \text{Effect of } T \text{ on } Y = \frac{\text{reduced form}}{\text{first stage}} = \frac{E(Y_i|Z_i = 1) - E(Y_i|Z_i = 0)}{E(T_i|Z_i = 1) - E(T_i|Z_i = 0)}$$

Note: So we take the difference in average outcome between the two and how denominator is simply a scaling up: probability taking up if treated (55% this case, fraction of participants) – prob of taking if non treated (0% In this case).

**Bhatt, M. P., Heller, S. B., Kapustin, M., Bertrand, M., & Blattman, C. (2024). Predicting and preventing gun violence: An experimental evaluation of READI Chicago.**

<i>Component</i>	<i>Summary</i>
<b>Background</b>	Gun violence is a <b>critical public issue</b> in U.S. cities. Existing strategies emphasize aggressive policing and incarceration. This study investigates whether more efficient approaches are possible.
<b>Research Question</b>	(1) Can high-risk individuals be accurately <b>identified</b> and engaged? (2) Can a behavioral-economic program <b>reduce</b> their involvement in shootings?
<b>Challenges</b>	Problem is concentrated in some neighborhoods, and specifically in some groups of people = need targeted intervention. Challenges - <b>Identification:</b> complex observables and unobservables - <b>Engagement:</b> these individuals often distrust institutions, and face barriers (e.g., housing instability, addiction). - <b>Effectiveness:</b> Limited rigorous prior evidence.
<b>The Program (READI)</b>	<b>Randomized controlled trial</b> (N=2,456) in five high-violence Chicago neighborhoods. The program combined an 18-month <b>subsidized job</b> (intended primarily as an incentive to make people participate) with <b>cognitive behavioral therapy (CBT)</b> and <b>social support services</b> .  (1) <b>Algorithmic pathway:</b> Police data used to predict risk of being involved in gun violence as a victim or an arrestee. Limitations: miss risk driven by unobservables or fast-moving situations not captured by the data. (2) <b>Outreach pathway:</b> Referrals from experienced outreach workers with extensive on-the-ground experience. Such referrals may be capturing both unobservable risks and treatment responsiveness. (3) <b>Jail exit screening.</b> Some technical remarks: - Outreach workers did not prioritize the highest-risk individuals—75% had below-median risk. - Unobservables: Outreach referrals had higher realized risk than algorithmic ones at the same predicted risk, suggesting workers used unobserved factors in selection. - Take-up differences: Outreach referrals were 40 percentage points more likely to start READI than algorithmic referrals
<b>Selection Mechanism</b>	Overall take-up: 55%.
<b>Take-Up</b>	
<b>Empirical Strategy</b>	RCT comparing treatment and control. Primary outcome: composite index of (i) shooting/homicide victimizations, (ii) shooting/homicide arrests, (iii) other serious violent-crime arrests.
<b>Key Findings</b>	- The program was a success in identifying people at risk: in the control group, 11 shooting/homicide victimizations per 100 people over 20 months.



- No effect on the overall violence index.
- A 65% reduction in shooting/homicide arrests (unadjusted  $p=0.05$ ), but not significant after multiple testing correction.
- Participants referred by outreach workers—a prespecified subgroup—saw enormous declines in arrests and victimizations for shootings and homicides (79% and 43%, respectively) which remain statistically significant.
- Still, our exploratory analysis shows that only the outreach referrals with the highest algorithmic risk predictions respond to READI. So it is possible that a combination of human intelligence and machine-driven risk prediction may more effectively anticipate treatment responsiveness than either method alone.
- Spillovers: in violation of the SUTVA, which assumes that one person's treatment does not affect another's outcome.
- Robustness / Validity**
- CONCLUSIONS and policy implications**
- high-risk individuals can be identified and engaged (bc super concentrated)
- job support + CBT shows promise
- program more effective for outreach-referred participants

### Ex. 1 PROGRESA

DETAILS	
BACKGROUND	Large-scale experiment conducted in Mexico 30 years ago, a developing country with huge problems of poverty and education attainment.
EXPERIMENT	Idea: give a cash transfer to poor families <b>conditional on the fact that kids keep going to school. Pilot on restricted sample of communities (RCT)</b>
BALANCE TEST	The <b>difference in balance between the two groups is always very small</b> . But <b>2 p-values are below 0.01 or 0.05</b> : is this a problem? <b>No</b> , because it's only <b>two variables out of many</b> (false positives are expected).
RESULTS	<b>Effective</b> , decided scale up!
EXTRA (BOBONIS ET AL.)	Exploiting the PROGRESA experiment, they <b>estimate the impact of receiving the cash transfer on domestic violence</b> : ATE 5% statistically significant

### Ex. 2 Policing experiments

Idea and methodology:

- Want to see if higher policing reduces crime.
- Idea: identify 120 foot patrol areas and pair them based on similar crime rates. One area from each pair was randomly assigned to the treatment group (receiving foot patrols).
- Radcliff et al. found that foot-patrolling in Philadelphia was effective.

General issues with patrolling experiments:

- SUTVA is violated (spillovers): Criminals in treated areas move and start committing crimes in Control areas (indeed crime in hotspots with less foot-patrolling saw an increase in crime)
- if you reduce officers in control to send in treatment, then the control is not control anymore but rather treated also because you are reducing police officers there (again, sort of same problem as before).

## D. Pros and Cons of RCTs

### 1.1 Advantages of RCTs

- **High internal validity:** if properly executed, RCTs provide consistent estimates of the treatment effect.
- **Simple and intuitive:** identification relies on comparing average outcomes across treatment and control. Easy to explain to the public.
- **Allow for manipulation of reality:** enables the study of complex causal mechanisms (eg. via multiple treatment arms).
- **Force researchers to dive into reality:** researchers must confront organizational issues and collaborate with governments and NGOs.

### 1.2 Potential Problems of RCTs

- **Limited external validity:** findings may not generalize beyond the experimental context.
- **Implementation sensitivity:** small mistakes in execution can undermine validity.
  - **Hawthorne effect:** participants alter behavior when they know they are being observed (e.g., increased productivity in monitored workers).
  - **John Henry effect:** control group competes with treatment group when aware of the intervention (e.g., schools trying to outperform treated ones).
- **Costly**
- **Ethical concerns:** a coin flip determines who receives life-saving medicine.
  - Note: Despite ethical concerns, randomization may be the most democratic method of assigning treatment.
- **Practically unfeasible** (ex. mafia bosses)

## 2 Natural Experiments

- Not under the direct control of the researcher.
- A treatment and a control group
- Treatment assignment that is “as good as random” (justify)

---

\*Remark: Why not simply matching on observable characteristics?



**Prince Charles**

- Male
- Born in 1948
- Raised in the UK
- Married twice
- Lives in a castle
- Wealthy & famous



**Ozzy Osbourne**

- Male
- Born in 1948
- Raised in the UK
- Married twice
- Lives in a castle
- Wealthy & famous

## CHAPTER 3: DETERRENCE EFFECT

**Background:** Prison serves two key functions: incapacitation (preventing crime during imprisonment) and deterrence (discouraging future offenses).

**Research question:** How strong is the deterrence effect? That is, by how much higher expected prison sentence deter crime?

- Expected prison sentence ==>> crime rate
- Example: The deterrence effect is the following: out of 10,000 individuals, if they know they will get k years of prison, 10 will commit a crime. If they know that will get k + 5 years, 5 of them will commit crimes.

**Challenges:** Estimating pure deterrence effects requires exogenous variation in expected punishment (Ideal experiment: randomly assign sanctions (and let potential offenders know in advance!)). But:

- i. You do not observe expected sentence before the crime, but **actual sentence after crime**
- ii. Irrational expectations: Criminals expectations about sentence not only are unobserved, but also criminals themselves do not know it (depends on how the robbery goes, how severe the judge etc...). So the idea is that we cannot see the treatment (opposite case would be to estimate effect of money subsidy, you exactly see the subsidy)!
- iii. You observe a record of criminals & **Actual sentences after crime**. Clearly subject to OVB (Sanctions depend on individual characteristics (selection bias)): Judges give repeat offenders / more dangerous individuals harsher sanctions. So we see higher sentences being positively correlated with repeated crimes.

### Preliminary evidence:

- In the US there was a strong increase in incarceration rate (policy driven, from 80s onwards). Did higher imprisonment rate lead to less crime?
- Contrasting evidence: time series (yes, more incarceration less crime) vs cross sections (no, more incarceration more crime) => Need an RCT or a natural experiment!

### The Natural Experiment: Drago, Galbiati, Vertova (2009) — The Deterrent Effects of Prison: Evidence from a Natural Experiment

COMPONENT	SUMMARY
RESEARCH QUESTION	How strong is the deterrence effect of longer expected prison sentences on recidivism?
BACKGROUND	<p>Italian prisons are traditionally overcrowded. To fix this in 2006 (overcrowding at 140%) the Italian gov passed a collective clemency bill ("indulto"). Around 22,000 inmates (~40% of Italy's prison population) were released August 1, 2006:</p> <ul style="list-style-type: none"> <li>- All individuals with less than 3 years of residuals sentence were freed from prison.</li> <li>- BUT, KEY: if you were re-arrested within 5 years, the pardoned residual sentence (between 1-36 months) adds to the new sentence</li> </ul>
NATURAL EXPERIMENT	<p>Indulto is a perfect natural experiment to test the deterrence effect:</p> <ul style="list-style-type: none"> <li>- Take inmates arrested for the same crime with the same original sentence length but in two different periods of time.</li> <li>- Conditional on original sentence length, variation in residual sentences (the key deterrence margin) depends only on prison entry date, plausibly random!</li> </ul>

	Treatment group (Elwood): conditional on original sentence length residual sentence above the median (if rearrested stays for longer) Control group (Jake): residual sentence below the median																																																																		
BALANCE TEST	Balance test: compare pardoned inmates with above median vs pardon inmates with below median residual sentence. A closer inspection of the data corroborates this intuition: conditional on the original sentence length, inmates' observable characteristics are balanced for individuals below and above the median of the remaining sentence.																																																																		
DEPENDENT VARIABLE	Now we can observe the effect of different expected punishing! Main outcome of interest: probability of recidivating before February 2007 (7 months after the 'Indulto'). If there is a deterrence effect Elwood should recidivate less than Jake.																																																																		
DATA	Administrative data (DAP) on 25,814 inmates released between August 2006 and February 2007, including recidivism status (up to February 28, 2007) and rich individual-level covariates.																																																																		
RESULTS	For each group with same original sentence, T vs C, plot the average recidivism. The Idea is so good you immediately see the effect (a good paper does not necessarily need extremely complex methodologies <sup>②</sup> ).																																																																		
	<p>The chart displays the average recidivism rate across various original sentence lengths (23 to 43 years). The y-axis represents the Average Recidivism percentage, ranging from 0% to 10%. The x-axis lists the original sentence lengths. For each length, there are two bars: a black bar for 'below median residual sentence' and a white bar for 'above median residual sentence'. The 'below median residual sentence' group consistently shows higher recidivism rates than the 'above median residual sentence' group, particularly for longer sentences (e.g., 25, 32, 34 years).</p> <table border="1"> <thead> <tr> <th>Original Sentence</th> <th>below median residual sentence (%)</th> <th>above median residual sentence (%)</th> </tr> </thead> <tbody> <tr><td>23</td><td>~10</td><td>~5</td></tr> <tr><td>24</td><td>~12</td><td>~5</td></tr> <tr><td>25</td><td>~15</td><td>~5</td></tr> <tr><td>26</td><td>~10</td><td>~5</td></tr> <tr><td>27</td><td>~12</td><td>~5</td></tr> <tr><td>28</td><td>~10</td><td>~5</td></tr> <tr><td>29</td><td>~10</td><td>~5</td></tr> <tr><td>30</td><td>~10</td><td>~5</td></tr> <tr><td>31</td><td>~12</td><td>~5</td></tr> <tr><td>32</td><td>~15</td><td>~5</td></tr> <tr><td>33</td><td>~10</td><td>~5</td></tr> <tr><td>34</td><td>~15</td><td>~5</td></tr> <tr><td>35</td><td>~10</td><td>~5</td></tr> <tr><td>36</td><td>~12</td><td>~5</td></tr> <tr><td>37</td><td>~10</td><td>~5</td></tr> <tr><td>38</td><td>~12</td><td>~5</td></tr> <tr><td>39</td><td>~10</td><td>~5</td></tr> <tr><td>40</td><td>~10</td><td>~5</td></tr> <tr><td>41</td><td>~10</td><td>~5</td></tr> <tr><td>42</td><td>~10</td><td>~5</td></tr> <tr><td>43</td><td>~12</td><td>~5</td></tr> </tbody> </table>	Original Sentence	below median residual sentence (%)	above median residual sentence (%)	23	~10	~5	24	~12	~5	25	~15	~5	26	~10	~5	27	~12	~5	28	~10	~5	29	~10	~5	30	~10	~5	31	~12	~5	32	~15	~5	33	~10	~5	34	~15	~5	35	~10	~5	36	~12	~5	37	~10	~5	38	~12	~5	39	~10	~5	40	~10	~5	41	~10	~5	42	~10	~5	43	~12	~5
Original Sentence	below median residual sentence (%)	above median residual sentence (%)																																																																	
23	~10	~5																																																																	
24	~12	~5																																																																	
25	~15	~5																																																																	
26	~10	~5																																																																	
27	~12	~5																																																																	
28	~10	~5																																																																	
29	~10	~5																																																																	
30	~10	~5																																																																	
31	~12	~5																																																																	
32	~15	~5																																																																	
33	~10	~5																																																																	
34	~15	~5																																																																	
35	~10	~5																																																																	
36	~12	~5																																																																	
37	~10	~5																																																																	
38	~12	~5																																																																	
39	~10	~5																																																																	
40	~10	~5																																																																	
41	~10	~5																																																																	
42	~10	~5																																																																	
43	~12	~5																																																																	
COST-EFFECTIVENESS	Regression Result: + 1yr expected sentence $\rightarrow$ -16.5% recidivism! Controls are almost irrelevant: It is a good experiment, controls have very low effects																																																																		

### What about Peer effects?

I. Individual decision to commit crime influences peers' criminal behavior:

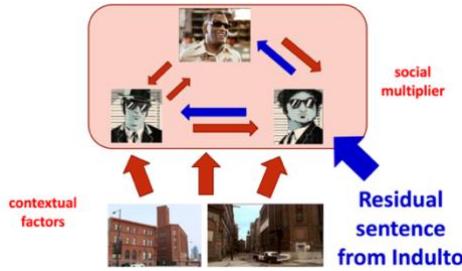
- Same as in education, employment, etc. or use of drugs
- Can generate social multipliers = multiple equilibria, extreme variability in crime. Ex. two same restaurants, one always full one empty
- Important policy implications

II. Peer effects are hard to identify:

- Reflexion problem: when one tries to predict the behavior of an individual by the behavior of the group of which the individual is a member. Is the individual affecting the behavior of the group, or is the group affecting the behavior of the individual?
- Contextual (i.e., omitted) factors: is peer effect or is due to the neighborhood where they live?

III. Well, let's see what happened with indulto

Indulto changes the behavior of Jake! Indulto is an exogenous measureable treatment in this system of relations!



Estimation methodology: Identified peers as Italians living in the same region / foreigners living in the same country

- main estimating equation for recidivism of individual  $i$  from place (region or country)  $k$  who served the sentence in prison  $j$

$$y_{ijk} = \beta_1 S_{ijk} + \beta_2 T_{ijk} + \beta_3 \bar{S}_{(-i)jk} + \beta_4 \bar{T}_{(-i)jk} + \phi' X_{ijk} + \delta' \bar{X}_{(-i)jk} + \varepsilon_{ijk}$$

- $S_{ijk}$  = original sentence of individual  $i$  from place  $k$  in prison  $j$
- $T_{ijk}$  = residual sentence of individual  $i$  from place  $k$  in prison  $j$
- $\bar{S}_{(-i)jk}$  = average original sentence of  $i$ 's peers
- $\bar{T}_{(-i)jk}$  = average residual sentence of  $i$ 's peers ← peer effects
- $X_{ijk}$  and  $\bar{X}_{(-i)jk}$  are control variables

Results: Magnitude of peer effects is as relevant as direct effect

#### CHAPTER 4: PRISON CONDITIONS

Di Tella & Schargrodsky (2013), "Criminal Recidivism after Prison and Electronic Monitoring" (JPE):

Category	Details
<b>Objective</b>	Evaluate whether <b>electronic monitoring (EM)</b> reduces <b>recidivism</b> compared to <b>prison</b> through a small pilot program run in Buenos Aires (1997–2007).
<b>Background</b>	<ul style="list-style-type: none"> <li>• Prisons are costly, overcrowded, criminogenic (peer effects, stigma)</li> <li>• EM allows home confinement with surveillance</li> <li>• Main concern: recidivism</li> </ul>
<b>Data</b>	Administrative records from Buenos Aires Penitentiary Service: 386 individuals assigned to electronic monitoring (EM), 23,976 individuals assigned to prison
<b>Main Outcome</b>	Recidivism
<b>Theoretical Effects</b>	<ul style="list-style-type: none"> <li>- <b>Prisons specific deterrence</b> (makes punishment more painful) ⇒ recidivism ↓</li> <li>- <b>Prisons as "schools of crime"</b> ⇒ recidivism ↑</li> <li>- <b>Electronic monitoring favors rehabilitation</b>, reduces social stigma ⇒ recidivism ↓</li> <li>- <b>Prisons ↓</b> ⇒ lower incapacitation effects (they may commit crimes)</li> </ul>
<b>Empirical Challenge</b>	<p>OVB! EM is <b>not randomly assigned</b> → potential <b>selection bias</b> (judges assign lower-risk offenders to EM)</p> <p>Ideal Experiment (RCT): randomly assign electronic monitoring (impossible).</p>
<b>Strategy 1: IV Approach</b>	<ul style="list-style-type: none"> <li>• <b>Z</b> = judge leniency (measured as % prior EM assignments, garantistas vs. mano dura.)</li> <li>• <b>T</b> = EM assignment</li> <li>• <b>Y</b> = recidivism</li> </ul> <p>allocation of offenders to different judges is random ⇒ Z is a valid instrument for T</p> <p>As always you need that:</p> <ul style="list-style-type: none"> <li>- <b>Z affects T (first stage):</b> the leniency of the judge affects the probability of being assigned to electronic monitoring</li> </ul>

	- <b>Z affects Y only through T (exclusion restriction):</b> by random assignment, it should be uncorrelated with other offender's characteristics (exclusion restriction)
<b>Result Strategy 1</b>	<b>2SLS estimation:</b> EM significantly reduces recidivism by <b>11–16 pp</b> (~50% of baseline)
<b>Strategy 2: Matching</b>	Compare EM to matched prisoners (age $\pm 6$ m, crime, entry date, duration, history) → similar effect: <b>EM ↓ recidivism.</b> <i>*Why so similar to IV? One possible explanation: Sample (for the IV) was on common pool (individuals almost already matched).</i>
<b>Scalability Caveat</b>	EM may work partly because it was unexpected ("lucky break") → if generalized, deterrent effect may fall. I expect to go to prison than I am lucky I am given a bracelet I behave well. But what if once I know I go on electronic monitoring the prob of committing first crime is higher?
<b>How it ended</b>	Argentinian program suspended after a few cases of offenders on electronic monitoring escaping and committing crimes. Crimes committed are very salient in the media. Crimes avoided by EM (counterfactual) remain unobserved

## B. Do better prison conditions improve recidivism?

Idea: use extreme variability in prison conditions in the world. Some indicators:

- Overcrowding (inmates/beds)
- Suicides
- Additional indicator of «fairness» of justice system: pretrial inmates

Open vs closed prison

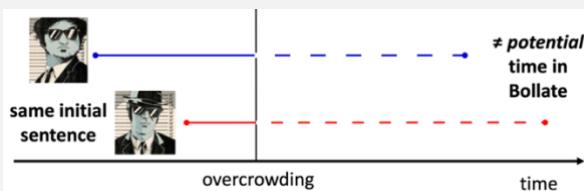
DIMENSION	CLOSED PRISON	OPEN PRISON
PHILOSOPHY	<b>Harsh conditions</b> deter recidivism	<b>Rehabilitation</b> curbs recidivism
FREEDOM	Inmates isolated; movements tightly regulated	<b>Life as normal</b> as possible within walls
TIME ALLOCATION	<b>Most of day in cell</b>	<b>Most of day outside cell</b>
DISCIPLINE	<b>Strict punishment for every deviation</b>	Little supervision
AUTONOMY	<b>No choice in daily life</b>	Inmates make decisions
ACTIVITIES	<b>Minimal</b>	Work, study, relationships
SOCIAL CONTACT	<b>Cut off from outside world</b>	Personal ties maintained

Do open prisons decrease recidivism? Hard to compare recidivism between open and closed prisons. Issues:

- cannot compare open vs closed prisons across countries: differences in prison size, costs, other country characteristics
- across individuals: non-random selection into open prisons (typically, dangerous criminals assigned to closed prisons)

**Mastrobuoni & Terlizzese, "Leave the Door Open? Prison Conditions and Recidivism", 2019**

Item	Description
<b>Research Question</b>	What is the <b>causal effect</b> of serving prison time in an <b>open-cell prison (Bollate)</b> versus a <b>closed-cell prison</b> on <b>recidivism?</b>
<b>Bollate vs other prisons</b>	Idea: compare open prison near Milan (Bollate: kindergarten for children, can learn a job, there is a garden) vs. closed prisons in the same area. Again, issue of selection in the type of inmates sent to Bollate!
<b>Design</b>	Quasi experiment based on <u>displaced inmates</u> , who were <u>not selected into Bollate</u> but <u>transferred to Bollate</u> due to overcrowding. This enables a <b>quasi-random variation</b> in exposure to open-prison conditions.



Jake and Paul were in the same prison (Opera) and had been assigned the same initial sentence, but then due to overcrowding Paul was sent to Bollate.

The focus is on the intensive margin of the treatment – the length of the period spent in the open prison, conditional on the total years served – and exploit a variation in such margin that we show is as good as random. What you will estimate in the end is the impact of spending XX time in Bollate.

So our X is: potential time served in Bollate on the displacements orders due to overcrowding!

#### **Identification assumptions**

Research design: use potential time served in Bollate as an IV for actual time

- affects time actually served in Bollate (first stage) (First come first served basis). First stage is strong.
- is randomly assigned from overcrowding shocks + affects recidivism only through actual time (exclusion restriction)

*\*The potential time may exceed the actual one whenever inmates are later transferred from Bollate to other prisons, typically as a result of disciplinary measures, or when they are granted an early release (through home detention, monitored liberty or other forms of non-custodial sentence).*

#### **Balance test**

Balance test: displaced inmates are balanced, selected are not

#### **Main Outcome**

**Recidivism**, defined as **re-incarceration within 3 years**.

#### **Main Estimate**

Serving 1 year in an open prison instead of a closed one reduces recidivism by ~6%  
(from a base of ~40%).

#### **Heterogeneity**

- Larger effect for **less educated** inmates
- No effect for **violent** or **high-risk** individuals.

#### **Scalability Issues**

Effects may partly rely on selection and the **deterrent threat** of transfer back to closed prisons; effectiveness might fade if generalized to all prisons.

## CHAPTER 5: Briotto Presentation on job loss and criminality in Brasil

### Background:

- Job loss is a long term shock: not only earnings plummet for the first months but they stay lower for years.

### Preliminary evidence:

- Time series comparison (plot is on the slides): lower employment rate & higher crime rate.
- Previous literature: Somewhat weak evidence, with more recent studies using individual level variation yielding to some evidence.

### Idea:

DID between very similar people (check pre-trend) that lose their job at some point vs ppl that do not. Still not enough: The effect of job loss on income is difficult to estimate! What is people were similar UP TO THAT POINT but then something happened to some of them (ex. wife left them and they got depressed) and that's why some lost their job?

→ Solution: use Exogenous mass layoffs! You had 100 people in a factory. Suddenly due to financial distress the factory had to fire 50 of them.

\*Some issue with selective fairing? When large fractions of the workforce are dismissed, scope for selective firing is limited.

**PAPER 1: "The Effect of Job Loss and Unemployment Insurance on Crime in Brazil", Britto, Pinotti, Sampaio.**

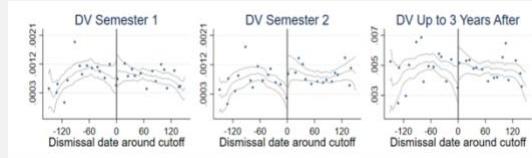
ITEM	DESCRIPTION
OBJECTIVE	Estimate the <b>causal effect of job loss on criminal behavior</b> and assess whether <b>unemployment insurance (UI)</b> mitigates this effect.
PLAN	1) Analyze the effects of job loss on crime exploiting mass layoffs and plant closures -> 2) Check spillovers on children, 3) effect of unemployment insurance (will use regression discontinuity), 4) Distinguish between alternative mechanisms
DATA	Not very high privacy protection in Brazil, you can get everything you know about work & proceedings of people, everything online: Name of the defendant, lawyers, state, court municipality, start date . Easy data linkagebecause 50% of brazilian names are unique!
PRELIMINARY EVIDENCE	
DESIGN	Empirical Strategy: - Did among full time, private sector, male workers - 18 to 50 years old

	<ul style="list-style-type: none"> <li>- <u>Treated</u>: displaced in mass layoffs in 2012-14 (central yrs so that we have data before on pre-trend + after)</li> <li>- <u>Control</u>: Not displaced in the same year. Exact match on state (27), birth cohort, hiring year, income (R\$200 bins), industry (9) and firm size (4).</li> </ul> <p>=&gt; 1,1 million successful matches</p> <p>Event study regression:</p> $Y_{it} = \alpha + \sum_{t=-P}^T \delta_t (Treat_i \times Time_t)_{it} + \mu Treat_i + \sum_{t=-P}^T Time_t + \varepsilon_{it}$ <p>Note that we are controlling for rolling time effects and that mu treat controls for Fixed difference between treated and control groups.</p> <p>What if they are selectively firing bad workers? = workers fired are different than the ones kept?</p> <p>Empirical strategy</p> <ul style="list-style-type: none"> <li>- Treated workers are matched to similar non-displaced peers on age, tenure, firm, and pre-layoff wages.</li> <li>- Event studies show parallel pre-trends, supporting exogeneity.</li> <li>- Difficult to be selective in a mass layoff</li> <li>- Use alternative stricter mass layoff definitions</li> </ul>
MAIN FINDING	Job loss causes a <b>23% increase in criminal prosecutions</b> , persistent for at least 4 years. Crime rate raises fast + is persistent
HETEROGENEITY; CRIME TYPES	Significant increases in all types of crimes. But: <ul style="list-style-type: none"> <li>- <b>economic crimes (+43%)</b></li> <li>- <b>violent crimes (+17%)</b>, and <b>non-economic crimes</b>(e.g., property damage, traffic violations). This suggests, on top of economic mechanisms, a role for psychological factors (generally when you get into economic crimes things can go bad)</li> </ul>
HETEROGENEITY	<b>Random forest</b> : Strongest effects for <b>young, low-tenure</b> individuals. Remarkably, area-level conditions do not seem to play a primary role in driving the results
SPILLOVERS	<b>Cohabiting sons</b> of displaced workers are <b>18% more likely</b> to commit crime; no significant effect on brothers or partners.
MECHANISM (GENERAL)	<p>Why does job loss increase crime? 4 hyps:</p> <ol style="list-style-type: none"> <li>1) <b>Income / liquidity effects</b>: “poverty is the mother of crime”</li> <li>2) <b>Lower crime opportunity cost (Becker model)</b> as you no longer have a job → increases crime</li> <li>3) <b>Time substitution</b></li> <li>4) <b>Psychological shock</b></li> </ol> <p>What could be effect of UI on crime?</p> <ol style="list-style-type: none"> <li>1) Positive income/liquidity shock → decreases crime</li> <li>2) Time substitution → increases crime (Increases the duration of unemployment)</li> <li>3) some incentive to work informally? = in illegal activities? → increases crime</li> </ol>
UI METHODOLOGY	<ul style="list-style-type: none"> <li>- UP to now we have been including everyone, both those getting UI and not.</li> <li>- Now Use a regression discontinuity on UI exploiting UI eligibility requirements. UI eligibility requirement: 16-month between layoffs for workers to receive again unemployment benefits</li> <li>- Balance test ok: around the cutoff covariates are balanced (no differential prosecution rates before job loss).</li> </ul>
UI EFFECT	<p>UI completely offsets job loss effect for Workers just eligible for UI, effect vanishes after expiration. Strongest for young = <b>liquidity-constrained</b> groups (confirms economic channel of job loss -&gt; crime).</p> <p>Conclusion: UI could have had 1 positive effect and 2 negative ones (see above). Since the overall effect is clearly opposite this means that effect 1 offsets everything and more. UI eligibility effect supports liquidity constraints as a primary mechanism! The fact the effect is strong for young an slow tenure is consistent to the liquidity constraints theory.</p>

### Robustness (he almost skipped in class)

- 1) Differential reporting ad prosecution across regions/time/workers groups, 2) lags in prosecution, 3) issues with police bias (police is more willing to arrest unemployed ppl) => use in flagrante cases!
- Selective firing: use stricter mass layoff definition

"Job Loss and Domestic Violence", Bhalotra, Britto, Pinotti & Sampaio (2021) <- don't know if included (check syllabus)

<i>Item</i>	<i>Description</i>
<b>Objective</b>	Estimate the <b>causal effect of male and female job loss on domestic violence (DV)</b> and assess whether <b>UI mitigates it</b> .
<b>Theoretical Models</b>	<ol style="list-style-type: none"> <li>1. <b>Household bargaining</b> (power in the household):           <ul style="list-style-type: none"> <li>• Male job loss ↓ DV; Female job loss ↑ DV</li> </ul> </li> <li>2. <b>Backlash/control</b>:           <ul style="list-style-type: none"> <li>• Male job loss ↑ DV; Female job loss ↓ DV</li> </ul> </li> </ol>
<b>Key Finding</b>	Found that, Contrary to both models, both <b>male and female job loss increase DV</b> .
<b>Mechanisms</b>	<ol style="list-style-type: none"> <li>1. <b>Income loss</b> → stress/conflict</li> <li>2. <b>Increased exposure</b> (time spent together) during unemployment</li> </ol>
<b>Unemployment Insurance (UI)</b>	<p>What is the effect of UI?</p> <p>Theory:</p> <ul style="list-style-type: none"> <li>- UI increases income and increases exposure (less weeks worked)</li> <li>- Job loss reduces income and increases exposure</li> </ul> <p>• UI <b>does not reduce DV</b> post-job loss    • DV <b>rises in semester 2</b>, when <b>UI expires</b>    • Over 3 years, UI eligibility ↑ DV lawsuits by ~33%</p> 
<b>Explanation</b>	<ul style="list-style-type: none"> <li>• <b>Semester 1</b> (with UI): income &amp; exposure effects offset</li> <li>• <b>Semester 2</b> (post-UI): income drops, exposure persists</li> </ul>
<b>Policy Implication</b>	UI is <b>ineffective</b> and actually backfires

Issue: Are we observing a real increase in violence, or just an increase in reporting? what if changes in reported domestic violence cases are due to shifts in the victim reporting behavior rather than actual changes in violence levels (fear / economic dependence)? Checks:

- (i) Violence Intensity: minor cases are more sensible to changes in reporting, focus on severe cases.
- (ii) 'In Flagrante' Cases (DV incidents caught in the act)
- (iii) Mandatory DV Notifications in Healthcare

**PAPER 2. Britto, Hsu, Pinotti & Sampaio. "Small children, big problems: Childbirth and crime** <- don't know if included (check syllabus)

<i>Item</i>	<i>Description</i>
<b>Objective</b>	Estimate the causal effect of <b>childbirth on crime</b> , focusing on both <b>mothers and fathers</b> , in a <b>developing country context (Brazil)</b> .
<b>Background</b>	<ul style="list-style-type: none"> <li>- In the U.S., parenthood is seen as a <b>turning point</b> reducing crime (esp. for fathers).</li> <li>- But in Brazil, childbirth may <b>increase financial stress</b> and crime.</li> </ul>
<b>Empirical Strategy</b>	<p><b>Difference-in-differences (DiD):</b></p> <ul style="list-style-type: none"> <li>- <b>Treated</b>: first-time parents (2011–2013)</li> <li>- <b>Control</b>: future first-time parents (<math>\geq 2</math> years later)</li> </ul> <p>Treated and control individuals are matched on cohort, gender, child gender, location.</p> <p><i>Remark: Childless couples are not used to avoid selection bias (Childbirth is endogenous: Couples who never have children may be systematically different from those who do (e.g., different income levels, relationship stability, life priorities))</i></p>

Main Findings	<ul style="list-style-type: none"> <li><b>Fathers:</b> crime ↑ +15% during pregnancy, +30% two years after birth</li> <li><b>Mothers:</b> sharp -60% drop around childbirth (short-lived)</li> </ul> <p>Effects driven by economically motivated crimes; no effect on non-economic crimes</p>
Mechanisms	1. <b>Financial stress</b> → DV and property crime ↑ (especially in low-income families) 2. <b>Increased exposure</b> (couples spend more time together post-birth)
UI	Does mothers' access to maternity benefits reduce fathers' criminal behavior?
Design	<b>Regression discontinuity (RD):</b> exploit eligibility cutoff for maternity benefits
RD Validity	<b>Fathers are balanced</b> around the cutoff (no manipulation)
RD Result	Reduction

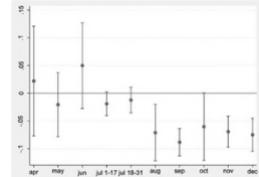
## CHAPTER 6: THE EFFECTS OF POLICE ON CRIME

### PART A: Does police reduce crime?

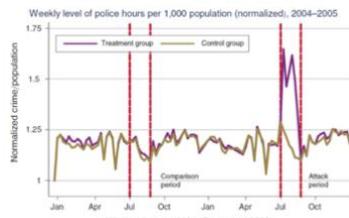
What we expect: More police in the streets (or more effective policing strategies) → increase in p. of being arrested → less crime  
Identification problem: **reverse causality** more police is assigned to places with higher criminality. This is why you see a positive relationship crime-police. Plus, **OVB**.

### PAPER: Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack, Rafael Di Tella and Ernesto Schargrodsky\*

- Idea: Following a terrorist attack on the main Jewish center in Buenos Aires, Argentina, in July 1994, all Jewish institutions received police protection. Thus, this event induced a geographical allocation of police forces that can be presumed exogenous in a crime regression.
- Result: Using data on the location of car thefts before and after the attack, we find a large local deterrent effect of observable police on crime.



### PAPER: "Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks", Draca, Machin, Robert Wilt\*

ITEM	DESCRIPTION
OBJECTIVE	Estimate the <b>causal effect of police presence on crime</b> , using the <b>exogenous shock</b> of the <b>2005 London terrorist attacks</b> and subsequent <b>police surge</b> .
DESIGN	Natural experiment using <b>Operation Theseus</b> : a sudden, temporary ( <b>6-week</b> ), <b>34% increase</b> in police presence in 5 central London boroughs. Compare with unaffected boroughs. Treated area (more policing) vs Control (27 boroughs), all relative to previous years (to remove seasonality <sup>*1</sup> , see image on the left). Essential: police was not diminished in control areas.
DATA	 
METHOD	<b>Difference-in-Differences (DiD)</b> with borough × week panel
MAIN RESULTS	<ul style="list-style-type: none"> <li>Police presence ↑ → <b>crime ↓ 11%</b> during deployment</li> <li>Crime rates quickly returned to pre-attack levels after the six week "policy-on" period</li> <li>No evidence that crime moved to other boroughs..</li> </ul>

<sup>\*1</sup> In summer there is a reduction in police patrolling, likely due to holidays.

CRIME TYPE EFFECTS	Effects strongest for <b>thefts and violent crimes</b> (visible, public), not for <b>burglary/sexual crimes</b> (private, less police-deterrable)
TUBE USAGE	↓ ~22% during Theseus; but: Importantly, on timing, notice that reduced use of the tube persisted and carried on well after the police numbers had gone back to their original levels. If the change in travel patterns induced by the terrorist attacks was responsible for reducing crime, then we would expect some part of this effect to continue after the deployment.
IDENTIFICATION VALIDITY	<ul style="list-style-type: none"> <li>• Uses <b>sharp on/off timing</b> of police surge</li> <li>• No evidence of <b>displacement (spatial/temporal)</b></li> <li>• <b>Placebo tests</b> show effects only in 6-week period</li> </ul>
KEY CONTRIBUTION	Provides <b>clean, credible evidence</b> that <b>visible, intensive police presence</b> causally reduces crime in urban public areas.

## PART B: Does predictive policing work?

### Comparison of Predictive Policing Approaches

Feature	COMPSTATS ( <i>Hot Spots</i> ) – U.S. Model	KeyCrime – Italian Model
<b>Core Idea</b>	<ul style="list-style-type: none"> <li>• Analyze crime data to find high-crime areas (“hot spots”)</li> <li>• <b>Deploy police</b> in those areas</li> </ul>	<ul style="list-style-type: none"> <li>• Analyze patterns across crime series to identify <b>repeat offenders</b></li> <li>• Predict where/when <b>same offender</b> will strike again</li> </ul>
<b>Target</b>	<b>Locations</b> (hot spots)	<b>Individuals</b> (unknown offenders identified via patterns)
<b>Key Tools</b>	Crime statistics by location	<ul style="list-style-type: none"> <li>• Crime pattern analysis using:             <ul style="list-style-type: none"> <li>↳ Forensic data</li> <li>↳ Modus operandi</li> <li>↳ Behavioral features (voice, clothing, handedness, language)</li> <li>↳ Time, location, and target type consistency</li> </ul> </li> </ul>
<b>Initial Knowledge</b>	<u>Crime areas are known; offenders are unspecified</u>	<u>Offender is unknown at first, but patterns help identify and anticipate their next moves.</u>
<b>Observed Effects</b>	<ul style="list-style-type: none"> <li>• Hot spots often overlap with <b>low-income, majority-Black</b> areas</li> <li>• <b>Community backlash</b> due to aggressive policing (e.g., stop-and-frisk)</li> <li>• Criminals <b>avoid</b> monitored zones</li> </ul>	<ul style="list-style-type: none"> <li>• Individual-based targeting avoids area-based over-policing. You are targeting just the criminal (e.g. wait outside the pharmacy, if the criminal strikes you arrest him).</li> </ul>
<b>Main Issue</b>	You stop random people	
	<b>High Displacement Effect:</b> Crime moves	<b>Low Displacement Effect:</b> Crime ends with arrest
<b>Strategic Focus</b>	<b>Place-centric</b> policing	<b>Offender-centric</b> policing

\*Additional Benefit of keycrime: Once an offender is caught, KeyCrime links them to their entire crime sequence → leads to longer sentences and improved deterrence.

### How effective was Keycrime? “Crime is Terribly Revealing: Information Technology and Police Productivity

Giovanni Mastrobuoni, Review of Economic Studies (2020)

Aspect	Description
<b>Objective</b>	Does predictive policing improve police Clearance rate? Estimate the <b>causal impact (KeyCrime)</b>
<b>KeyCrime</b>	KeyCrime tracks <b>crime sequences</b> (esp. robberies) to identify patterns. Predictive software suggests when, where, how robberies will occur.
<b>Setting</b>	Milan, 2008–2011 (2,167 commercial robberies). Two coexisting police forces: <ul style="list-style-type: none"> <li>• <b>Polizia di Stato</b> (uses KeyCrime) → <b>treated</b></li> <li>• <b>Carabinieri</b> (does not) → <b>control</b></li> </ul>
<b>Identification</b>	Exploits a <b>quasi-experimental setting</b> : <ul style="list-style-type: none"> <li>• Both forces have <b>same size, equipment, and training</b></li> <li>• Quasi-random assignment of robberies via 6-hour rotating shifts across 3 city sectors.</li> <li>• Use DiD. One group is treated the other no. Extra Twist: KeyCrime tracks crime sequences (esp. robberies) to identify patterns. We expect polizia to get better and better as the crime streak increments.</li> </ul>

**Main Results**

We find exactly what we expected:

- Clearance rate increases by 8 p.p. (from ~14%) for Polizia
- No effect for Carabinieri
- Stronger effect as number of crimes in sequence increases!

Extra evidence: For Polizia, clearance rate jumps from <5% to >15% if the robbery happens one day later, as this allows Polizia to have time to process info. No such jump for Carabinieri.

**Learning Offset**

- Criminals exhibit learning-by-doing: For the Carabinieri, clearance rates decline as the number of past robberies increases (i.e. repeat robbers become harder to catch). This indicates a learning effect by criminals ("The Polizia collects this information for the universe of reported commercial robberies that take place in Milan, even for those robberies that are investigated by the Carabinieri.")
- However, KeyCrime reverses this trend: For the Polizia using KeyCrime, clearance rates increase with the number of past robberies in the sequence. That is, predictive policing improves as more data are accumulated, overcoming the learning advantage of repeat offenders.

**Displacement effect**

No rise in other crime types or in the rest of the province.

Bank robberies fell from 1.4 to 0.5 per 100k (2008–2011) in Milan, a sharp and abrupt reversal of a previously increasing trend.. Synthetic control: LASSO-weighted cities confirm crime drop is unique to Milan.

Over time criminal groups tend to select the same business types, around the same time of the day, and in the same city neighbourhood,. 70% Probability that the next robbery targets the same business type as past ones in that robbery group (conditional probability, vs 5% marginal). 34% wrt the area.

## CHAPTER 7: ORGANIZED CRIME

### 1. Background

- Organized crime is not just crime: it is an parallel way of organizing society that challenges the main features and the power the modern state:

- Faster easier to **fix problems when state is absent** (eg way to find a job): the Sicilian Mafia filled the void of legal enforcement and trust in Southern regions in the wake of the Italian unification (Gambetta 1993).
- They **supply illicit goods** (Schelling, 1971).
- **State should have the monopoly of violence**, but organized crime also does.

### 2. Issues

A. Challenges of studying crime are amplified when studying organized crime:

- **Measurement issue:** People don't want to talk about organized crime -> great underreporting;
- It is impossible to run RCTs with organized crime

=> Until 10 years ago there was no large-scale data on organized crime. Only a lot of narrative evidence, judicial evidence.

B. How do we estimate mafia presence?

- 1) **Use convictions/prosecutions for mafia 416-bis** (from 1982 416-bis they coded in as a crime being part of a criminal organization. As long as you were not performing the activity ut us belonging to the organization you could not be convicted). Issues: the stronger the organization the less judges and police would report them. A spike could be weakening of criminal organization and reaction by the state. Ex. similarly happened in Tangentopoli as a reaction of the state 2
- 2) **Homicide rates**

### 3. Two empirical questions:

- a. **Whether and how mafias can migrate to other areas:** they were born in Sicily, etc. but can they replicate their nature/structure in other different cities/countries?
  - Some say that they cannot because there is something inherent in Sicilian culture; historical conditions (Borbons etc)
  - Others say yes, look at Milan.
- b. **What is the economic impact?**
  - I. "Mafias create jobs. Without organized crime, unemployment in southern regions would be much higher..." This position is much heard and considered. What if Mafia:
    - Creates jobs in the UNOFFICIAL ECONOMY
    - May attract public investment by corrupting politicians to finance their projects
    - Usually distributes wealth to poor people
  - II. But how many jobs are instead killed in the Legal Economy? We should also think about the **counterfactual** work and compare it to the factual to measure the economic cost of org crime. How to have the counterfactual? CENSIS (survey of entrepreneurs): it is a counterfactual, what damage is caused to your company by organized crime? Bah underpoepregn (Calabria below Puglia, weird. There is risk of underreporting (for fear) + how can they really know exactly?).

#### A. General Results

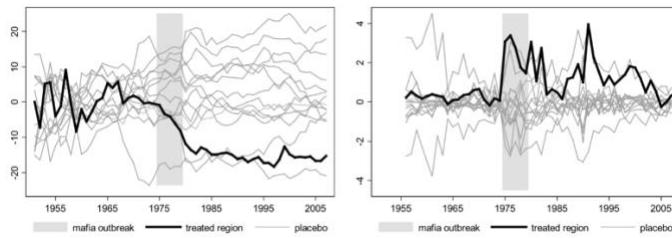
- If you plot the presence of **org crime against gdp per capita** -> negative relationship (again Italy is an outlier)

- If you try to split the **relationship between the different components of GDP** (as identified in Solow: L, K and TFP) and organized crime such relation is always negative.
- **Negative effect on political stability, positive effect on corruption**
- **Relationship with homicides**, not surprisingly

### C. How much does org crime cost?

The Economic Costs of Organized Crime: Evidence from Southern Italy, Author: Paolo Pinotti (2012)

ASPECT	DESCRIPTION
OBJECTIVE	Estimate <b>causal impact</b> of organized crime (mafia) on <b>regional economic development</b> .
IDENTIFICATION STRATEGY	<b>Apulia</b> and <b>Basilicata</b> , two non-historical mafia regions, saw <b>sudden mafia expansion</b> in the <b>mid-1970s</b> . These regions are treated.
RATIONALE	Quasiexogenous historical shock. Mafia infiltration in Apulia and Basilicata due to combination of circumstances: <ul style="list-style-type: none"> <li>- Closure of Tangeri port (1959-60) =&gt; diversion of tobacco smuggling from western routes (morocco -&gt; Sicily/Campania -&gt; Marseilles) to eastern routes (Apulia -&gt; Yugoslavia, Cyprus, turkey...). Smuggling becomes the biggest criminal business. Criminals from Puglia create a new crime organization (Santa Corona Unita) in Puglia. Then a major war between organizations from other regions selling tobacco happens.</li> <li>- 1980: earthquake in Irpinia -&gt; public funds to Basilicata, and the region was surrounded by all regions with criminal organizations</li> <li>- mafiosi from other regions sent to “confino” or in jail</li> </ul>
PROXY FOR MAFIA PRESENCE	Mafia membership (416-bis) legally defined only <b>after 1982</b> → <b>use homicide rate</b> as a proxy: sharp 4-5x increase in Apulia & Basilicata in 1975 (from ~1 per 100k). Sardinia outlier (Sardinia, because there was anonymous sequestering).
DATA	Panel: 1951–2007. <b>Pre-treatment:</b> 1951–1976. SCM is <b>trained</b> on 1951–1961 and <b>validated</b> on 1961–1975. The synthetic control perfectly matches GDP in pre-treatment → confirms quality of counterfactual. <b>Post-treatment:</b> 1977–2007. Variables: GDP per capita, electricity use, public/private investment, homicide rates, population.
OUTCOME VARIABLE (Y)	<b>GDP per capita</b> for Apulia + Basilicata.
EMPIRICAL STRATEGY	Synthetic Control Method (SCM): Compare GDP of treated regions (Apulia, Basilicata) to synthetic controls (construct a counterfactual using a weighted average of unaffected regions, donor pool). Control group: All Italian regions excluding historical mafia regions (Sicily, Campania, Calabria). Variables matched: For each region, collect: average GDP (1951–60), initial values of: investment rate, human capital, population density, sectoral shares (in 1960). Control units are weighted such that their pre-treatment characteristics (e.g., gdp per capita) resemble those of the treated unit as closely as possible. Control because is of control region; synthetic bc measure that does not exist in reality, but its aggregated one. *validation: how good is the synthetic control in replicating the treated regions if no treatment were applied. Until 1975 the synthetic control does perfectly, then a divergence occurs -> can interpret synthetic control as counterfactual. There is no dummy switched on, there is a divergence wrt a tuned control.
MAIN EFFECT	After 1975, treated GDP diverges from synthetic control. Estimated loss: <b>~16% lower GDP per capita over 30 years</b> (vs. synthetic).
ROBUSTNESS	- Alternative control weights, matching windows. - Other outcomes: <b>electricity consumption</b> shows similar decline (rules out “hidden economy” hypothesis).
PLACEBO TESTS	• Placebo test: the other lines are the placebos = replicate the exact analysis but with other treated regions (try to treat the other regions with the dummies). The estimate for the other treated regions is worst for the true treated regions, except Sardinia (strange case, judges was not considering a criminal org anonymous sequestering). This is a different way of constructing a confidence interval..



MECHANISM 1	<b>Drop in private investment</b> (documented in regional accounts). Public capital crowd-in: increase in <u>less productive</u> public investment (e.g. post-earthquake funds). Growth accounting shows shift in capital composition.
KEY ASSUMPTION	<b>Mafia entry is exogenous</b> to pre-existing trends. Supported by crime data (homicides), judicial sources, and sudden divergence post-1975.
CONCLUSION	Organized crime caused <b>persistent GDP loss</b> (~16%) in treated regions. Likely a <b>lower bound</b> , since: <ul style="list-style-type: none"> <li>control regions may still have minor mafia influence</li> <li>At the same time if some mafia in Puglia and Basilicata beg of period then out is a lower band effect.</li> <li>External validity: costs likely greater in Sicily, Campania and Calabria</li> </ul>

What was the Italia state doing to fight the mafia: 3 main policies: (29)

- **Carcere duro** for deterrence and to push more and more people to collaborate.
- **Seizures of mafia's assets:** seizing the assets of people **SUSPECTED** of being member of criminal org (even before the trial). Immediately after the start of judicial investigation.
- **City council dismissal:**
  - i). If a municipality is found/suspected to be infiltrated by Mafia (no need trial), all its public elected officials are dismissed and replaced by a team of external commissioners appointed by the central government. The commissioners have the same powers as the dismissed officials, and they govern the municipality for about two years until new elections.
  - ii). The law deems sufficient any evidence that suggests a connection between the Mafia and the local government (preventive purpose)

#### Paper 2. Organized Crime and Economic Growth: Evidence from Municipalities Infiltrated by the Mafia, Alessandra Fenizia, Raffaele Saggio\*

##### Background: What do the commissioners do?

Reviewing official reports of the interior minister to Parliament, external commissioners typically implement four types of interventions.

- i. Freeze all investment on new projects to conduct an initial review -> temporary ↓ public investment
- ii. Revoke public procurement contracts and permits obtained illegally or by means of connections to the Mafia
- iii. Change the municipal government's personnel practices (training, hiring). The official reports show that municipality bureaucrats are often poorly qualified and occasionally unco-operative.
- iv. Gain trust and support of local communities (e.g., free job training, sewage, aqueducts)

ASPECT	DETAILS
OBJECTIVE	Estimate causal effects of <b>anti-mafia city council dismissals (CCDs)</b> on local economic outcomes.
POLICY STUDIED	<b>CCD</b> = Dismissal of a municipality's entire political leadership (mayor + council) by central government, replaced by commissioners (2 yrs).
TREATMENT EVENTS	245 CCDs in Italy (1991–2016) triggered by <b>Mafia infiltration</b> .
DESIGN	<b>Matched Difference-in-Differences</b> using Italian social security data (INPS).
MATCHING STRATEGY	One-to-one <b>propensity score matching</b> across different <b>regions</b> (to avoid spillovers). This choice is corroborated by the presence of large spillovers from CCDs.
CONTROL VARIABLES (MATCHING)	Lagged log employment, earnings, industry shares, 1991 population.

MAIN DATA	employer-employee dataset (ISTAT), Real Estate Prices (Agenzia delle entrate), Local Politicians (Ministry of the Interior)
MAIN OUTCOMES (Y)	- Log employment - Log number of firms - Log wage bill - Log industrial real estate prices
KEY RESULTS	CCDs ↑ employment (+16.9%), ↑ firms (+9.4%), ↑ industrial real estate (+15%), ↓ <b>average wages</b> (-4.6%) in long run (t + 9).
MECHANISM EVIDENCE	<p>1. This first explanation is that CCDs lead to economic growth without, however, weakening the Mafia's presence.</p> <p>1a. Effects may be due to higher transfers by central gov (may have been...). No EVIDENCE</p> <p>1b. Second, we use CCDs that arise from factors unrelated to Mafia infiltration. As for Mafia-related CCDs the central government dismisses the local government and appoints experienced bureaucrats who administer the municipality until new elections. We find that these "alternative" CCDs generate much smaller economic effects. It thus appears that the re-centralization of power is not the main driver of our results.</p> <p>The second interpretation is that CCDs spur economic development because they erode the power of the Mafia.</p> <p>CCDs ↓ <b>mafia power</b> via: political turnover and dynamics. - Post-CCD politicians: younger, first-time, more women, more educated. All factors generally associated with lower levels of corruption. Interesting: show that CCDs do not affect the characteristics of political candidates running for local elections. In other words, CCDs do not affect who runs for office. They change who wins. This is indicative of a shift in voter preferences.</p> <p>Finally, we show that when CCDs fail to reduce the Mafia's presence, they are also unable to generate significant economic outcomes. We argue that municipalities that reelect politicians associated with the CCD are cities where the Mafia maintains a strong influence. These municipalities do not experience any significant economic growth post-CCD. As a result, the economic effects of CCDs materialize only in cities that experience a significant change in the composition of the elected officials following the dismissal of the city council.</p>
MECHANISMS – ECONOMIC	- Gains concentrated in mafia-prone sectors (e.g., <b>construction, waste</b> ). - <b>Connected firms</b> lose value and jobs post-CCD.
REAL ESTATE CONFIRMATION	↑ in industrial property values <b>confirms real economic gains</b>
SPILOVERS?	Concern with this analysis is that CCDs may benefit treated municipalities but displace organized crime to neighboring towns. We test this hypothesis and do not find evidence of negative spillovers. Actually positive spillovers
PLACEBO TEST	Effects are specific to CCDs due to mafia infiltration. Other reasons for CCDs: mayoral death/resignation/impeachment, resignation by half of city council, failure to pass a timely budget, public order, etc. <b>Mafia-unrelated CCDs:</b> small/no economic impact ⇒ real effects driven by weakening of mafia control.

## CHAPTER 8 - DO MAFIAS MIGRATE AND WHY?

### A. The 'confino' (reallocation) policy

Natural experiment in Italy: Confino. Hundreds of suspect (or convicted) members of criminal organizations re-settled from Southern regions to the Center North -> quasi-random assignment of organized crime presence

Background: Mandatory residence was a preventive measure (not a punishment): it was enough to be suspected or considered socially dangerous; no conviction was required. Consider that up to 1982 It was not possible to prosecute individuals for simply being members of a mafia-type criminal organization.

#### Rules:

- Resettlements were mandated by first-level trial courts. They were not in home detection. The idea is: the problem is in the south not in these people, in north cannot happen anything.
  - The mandate to reside in the assigned municipality could last between 1-5 years. No obligation to relocate back when the resettlement order expires
  - No explicit guidelines regarding the choice of the municipality, but mid-sized cities typically preferred both to small villages and to large metropolitan areas (Milan risky, but at least one police station to control and sign, 5-10k)
- Qualitative and journalistic evidence: made it easier for southern organizations to penetrate northern Italy

#### Qualitative and journalistic evidence:

EXAMPLE	KEY FACTS	CRIMINAL ACTIVITIES
1. BARDONECCHIA	<ul style="list-style-type: none"> <li>- 1960s tourism boom</li> <li>→ construction surge</li> <li>Ndrangheta acted as broker for illegal labor</li> </ul>	<ul style="list-style-type: none"> <li>- Labor racketeering (70–80% workforce)</li> <li>- Intimidation, extortion, murder of workers, entrepreneurs and local politicians (60s-70s)</li> <li>- 1995: City council dismissed for mafia infiltration (1st in Northern Italy)</li> </ul>
2. MALA DEL BRENTA	<ul style="list-style-type: none"> <li>- 1970s–</li> <li>1990s, active in Veneto</li> <li>- Only known <b>regional mafias</b> in Northern Italy</li> <li>- Origin: local burglars turned drug lords via ties to <b>confinati</b></li> </ul>	<ul style="list-style-type: none"> <li>- Narcotics trafficking</li> <li>- Extortion, loansharking</li> <li>- Arms trafficking, money laundering</li> </ul>
3. REGGIO EMILIA	<ul style="list-style-type: none"> <li>-</li> <li>1982: Antonio Dragone relocated from Calabria</li> <li>- Subsequent migration of more Ndrangheta affiliates</li> </ul>	<ul style="list-style-type: none"> <li>- Money laundering (construction, fake invoices)</li> <li>- Drug trafficking</li> <li>- Labor racketeering</li> </ul>

**How to study this? We have the perfect experiment! <- not included I think**

Ideal experiment: drop mafia people to random cities. Gov has done this!

#### Data:

- in general, lists of confinati were classified
- in 1975, a few such lists were discussed in the national Parliament -> info became publicly available
- 493 individuals sent to confino during the period 1961-72
- 399 confinati to centre-northern regions

#### Empirical strategy:

Weighted cross sec: Compare ‘assigned to treatment’ and ‘control’ cities relying on quasi-random assignment of confinati. Match cities on the basis of IPW, Entropy and Kernel weightin,

Just want ITT: 1) because there is no unambiguous measure of organized crime presence (actual compliance), 2) impose neither exclusion restriction nor monotonicity

Balanced but: the few Unbalances are related to the Political traditions of these municipalities: DC sent people to municipalities ruled by the socialists (my idea: DC majors asked party not to receive those criminals).

#### Results:

The “treated” communes have:

- more criminal associations and seized assets
- more homicides, beating and threatening
- more drug related crimes, more exortation, exploitation of prostitution and loansharking

## **B. Migration to the US and the birth of the Italo-American Mafia (to my understanding not in syllabus, so i cut and kept just key)**

### A. Historical Background

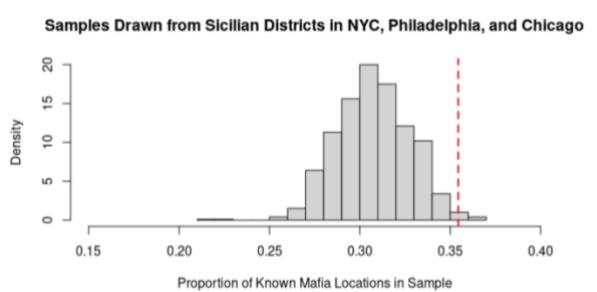
- **May 28, 1924:** Benito Mussolini grants **Cesare Mori**, the "Iron Prefect", full military powers to eliminate the Mafia.
- **January 1, 1926:** Siege of Gangi. In 1926 alone, **32 additional towns** classified as Mafia strongholds are raided by Mori.
- **Salvatore Lupo (2008):** Many mafiosi "used clandestine travel channels to escape the Mori hurricane."
- **1920s Prohibition Era:**
  - Nationwide alcohol ban → massive black-market demand.
  - High profitability and low initial state capacity to police it.
  - Sicilian mafiosi arrive with timing and skills ideal for supplying **“criminal capital”**

### B. Idea: map mafia bosses into Us cities.

#### 1) Effects on mafia presence

Issue: is it mori districts or is it Italian American districts? What if the "Mori" hexagons were just a random selection of equally Italian-American areas? Would we still see such a high overlap with mafia presence?

- Thought experiment (placebo): build a placebo distribution
- What is the expected proportion of mafia locations that would arise from a random sample of Italian-American/Sicilian districts?
- What is instead the actual observed proportion of mafia locations that are associated to a "Mori-district"?



#### 2) Effects on homicide rates before and after:

Mori neigh less homicides, but higher rate outside the mori districts! (standard result)

3) **Redlining:** Redlining had terrible consequences wrt employment college rate and puberty rate. Being a mori district increases p of redlining. So you expect them to be extremely poor. No! They were redlined but those districts were better than the others. Potential explanations (similar to drug cartels in Mexico):

- Proceeds from criminal activity (e.g. during Prohibition)
- Re-investment in the area (your own people), they took care of their own districts to keep people happy

## CHAPTER 9: IMMIGRATION AND CRIME

### Background:

Perceived concerns: there are too many immigrants, they increase in crime, steal jobs.

History: Longstanding issue: 1931 US report on crime and the foreign born.

- Nowadays, in the US, immigrants are less likely to be incarcerated than natives in the US (regardless of what Trump says).
- However, for Europe the case is more complex!
- Negative relationship between immigration and crime: criminal offenses decrease while immigration increases. However, both trends likely reflect long-run phenomena.

However, consider for example the percentage of immigrants out of the total population in prison in Italy: 30% vs 10% share out of the total population). Reason?

1. They may be committing more crimes
2. Discrimination (send Italians to home detention). Illegal immigrants go directly to jail bc have no official residence.

Clearly important factors to consider are income (and ability to pay a lawyer), educ, documents etc.

Ideal RCT: assigning legal status to random sample of illegal immigrants

Bianchi, Buonanno, Pinotti (2012) — *Do Immigrants Cause Crime?*

<i>Component</i>	<i>Summary</i>
<b>Background</b>	Immigration raises two key concerns: (1) labor market competition and redistributive effects (vs natives); (2) crime.
<b>Research Question</b>	Do immigrants causally increase crime rates in host areas?
<b>Data</b>	95 Italian provinces, 1990–2003. <ul style="list-style-type: none"><li>- Crime: Police-reported crimes (ISTAT)</li><li>- Immigration: Residence permits (Ministry of Interior)</li><li>- Controls: GDP per capita, unemployment, population, urbanization, male share (15–39), crime clear-up rates, local political orientation (left/right).</li></ul>
<b>Challenges</b>	<b>Selection bias/OVB:</b> When immigrants choose where to locate within the destination country, impossible to isolate (causal) effect of migration from other variables that are likely correlated with both immigration and crime: labor market conditions, housing prices, social capital, etc... Example: they migrate where houses cost less, but these neigh are already characterized by higher crime rates. -> ideal solution: randomly allocate migrants across areas  <b>- Measurement errors:</b> a) <u>Endogenous underreporting:</u> Suppose provinces with more immigrants also have: <ul style="list-style-type: none"><li>- Police that underreport crimes more (or less).</li></ul>

- Victims that are less likely to report crimes (fear, mistrust).
  - Type of criminal activity that is more underreported than others
- Then the relationship between immigration and crime is confounded by reporting behavior.

b) **Unobserved irregular immigrants may bias** (downward, more infra) estimates. Especially because irregular immigrants may be more likely to commit crime, for example due to exclusion, lack of legal work or self-selection: higher propensity to commit crimes are those who don't legalize.

BUT If the number of irregular immigrants is random, the error is classical measurement error → mainly attenuation bias.

Province A: 1,000 immigrants (all official).

Province B: 2,000 immigrants (800 official + 1,200 irregular).

Crime rate B = 10, Crime rate A = 5

Misleading picture:

A: 1,000 immigrants + low crime.

B: 800 immigrants + high crime.

Result: You wrongly conclude less immigration → more crime.

#### **Measurement Error Strategy**

- **Crime:** We control for the (unobserved) level for each province through dummies for regional areas and we control for the (unobserved) change in the measurement error across time that is common across regions. SEE PAGE 2 of these notes (possible solutions to measurement error).

- **Immigration:** as in the case of crime, logarithms and fixed effects may solve the problem. They model the number of total immigrants over the population as the sum of province and year fixed effects and the number of official immigrants (read carefully is clear).

Check 1: Subsequent regularizations of previously unofficial immigrants allowed to assess the accuracy of this proxy of the number of total immigrants in Italy. Then: reconstruct the log of total (official plus unofficial) immigrants over province population in the years in which there was a regularization, the measure is well proxied by the log of official immigrants on province- and year- fixed effects.

Check 2: Apprehensions refer to the arrest of individuals residing in a country without a valid permit; as such, they are not affected by self-selection. However, they show that apprehensions- and regularizations-based measures of unofficial immigration seem consistent with each other.

Plus, IV should above this if immigrants of the same nationality tend to cluster in the same areas

#### **Model**

$$\log(\text{Crime}_{it}) = \beta \log(\text{Immigrants}_{it}) + \gamma' X_{it} + \phi_i + \phi_t + \varepsilon_{it}$$

So, considering the measurement issues described above, the log of the true (unobserved) number of crimes over the population is modelled as a function of the log of number of total number of immigrants plus a set of control variables (socioeconomic and demographic determinants of crime), and year- and province-fixed effects.

#### **OLS Results**

A 1% immigration increase ⇒ 0.1% total crime rise. Driven by property crimes (robberies, thefts); no effect on violent or drug crimes. But possible upward bias due to unobserved pull factors.

#### **IV Strategy**

- **Aim:** instrument the shifts in the immigrant population across Italian provinces (arrivals of immigrants)

- **Logic:** New immigrants tend to settle in existing enclaves of their nationality (predictable allocation).

- **Source of exogenous variation:** (exogenous) supply-push component of migration, ex. war or natural disaster. measure supply-push factors using migration flows to other countries, not Italy (to separate push from pull factors). Exogeneity of the (european) pull factor: Demand-pull factors in other destination countries can be reasonably thought as exogenous to variation in crime across Italian provinces.

#### **Identification Checks**

Our instrument should: 1) Be correlated with the actual number of immigrants arrived but 2) uncorrelated with the current local outcomes in area i.

	<ul style="list-style-type: none"> <li>- <b>Relevance:</b> First-stage F-stat &gt; 13; partial <math>R^2 \approx 0.09\text{--}0.15</math>. Push factors correlate with Italian immigration flows.</li> <li>- <b>Exclusion restriction</b> plausible: migration to other EU destinations unlikely correlated with Italian provincial conditions.</li> </ul>
<b>IV Results</b>	<ul style="list-style-type: none"> <li>- Immigration has <b>no causal effect</b> on total, property, violent, or drug crimes.</li> <li>- Only <b>robberies</b> increase (significant, but &lt;2% of crimes)..</li> <li>- Remark: IV estimates are based on a subset of nationalities (only those for which they found Census data in Eurostat). So, if the excluded nationalities had a higher propensity to commit crime than those included in the instrument, this could cause the observed drop in magnitude and significance from OLS to IV.</li> </ul>
<b>Robustness</b>	<p>Results hold under:</p> <ul style="list-style-type: none"> <li>- Expanded instruments (e.g. OECD migration flows).</li> <li>- Restrict sample to immigrants from developing countries only (as defined by ISTAT).</li> <li>- Restricted OLS: They re-run the OLS using only the subset of nationalities included in the IV. Result: OLS coefficients are almost identical to full-sample OLS <math>\Rightarrow</math> Exclusion of nationalities not driving the difference.</li> <li>- Controls for irregular immigrants via regularization data</li> </ul>
<b>Mechanism</b>	<p>immigrants have worse job prospects <math>\uparrow</math> crime, Immigrants face harsher punishments <math>\downarrow</math> crime, Natives may be displaced (US case) <math>\uparrow</math> crime</p> <p>*The theory compares immigrants' incentives to commit crime relative to natives, because: The crime rate is defined over the whole population</p>
<b>Policy Implications</b>	<p>Immigrants do not increase overall crime rates; concerns over immigration-driven crime spikes are largely unsupported when causal identification is applied, so whether immigration increases crime depends on whether immigrants have higher or lower crime propensity than natives.</p>

### Legal vs. Illegal Immigrants

Illegal immigrants represent 30% of the immigrant population in Italy.

- Yet, they account for: 80% of serious crimes reported by police, 94% of incarcerated immigrants. Why?
  - First, consider that (balancing table): They are younger, male, less educated, and lower-income than legal immigrants, all traits statistically associated with higher crime propensity.
    - A. Lack of legal status  $\Rightarrow$  Exclusion from legal labor markets, Social marginalization, Higher economic vulnerability. Policy suggestion: Legalization reduces crime by integrating undocumented immigrants. BUT future inflows may increase if newcomers anticipate future amnesties.
    - B. Selection hypothesis: Illegal immigrants **differ inherently** from legal ones:
      1. They entered a country illegally, they are intrinsically different
      2. The probability of having legal status may depend on other individual characteristics that are also correlated with crime (e.g., labor market ability).
- Policy implication: Legalization **does not reduce crime**. Only **expulsion** or strict deterrence would lower crime rates.

Ideal Experiment: Randomly assign legal status to illegal immigrants.

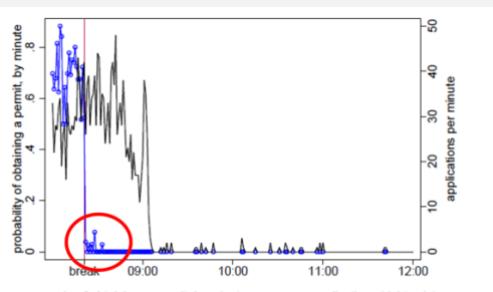
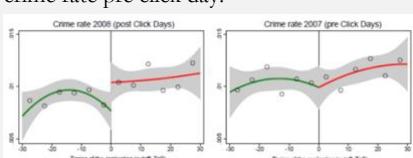
### Legal Status and the Criminal Activity of Immigrants Giovanni Mastrobuoni Paolo Pinotti (2015)

COMPONENT	DETAILS
RESEARCH QUESTION	What is the <b>causal effect</b> of <b>legal status</b> on immigrants' <b>criminal behavior</b> , specifically <b>recidivism</b> ?
MOTIVATION	Crime gap may reflect <b>selection</b> , not causality. Legal and illegal immigrants differ in observables (education, age, etc.) and unobservables.
NATURAL EXPERIMENT	EU <b>enlargement on Jan 1, 2007</b> gave <b>Romanians/Bulgarians</b> full legal status in Italy. Romanians and Bulgarians released in 2006 under clemency $\rightarrow$ illegal before Jan 2007, legal after EU entry (Treatment group). EU candidate countries (Albania, Serbia, etc.) $\rightarrow$ remained illegal (Control Group).
SAMPLE	Aug 2006, <b>Indulto</b> : 22,000 inmates released (1/3 of prison pop), incl. $\sim$ 9,600 foreigners. Our sample: $\sim$ 2,300 male inmates: 725 treated, 1,622 control.
KEY OUTCOME	<b>Reincarceration</b> (recidivism) tracked from Aug 2006 to Dec 2007.

ISSUE	<p>(I) We have number of crimes / official residents. Crime is always reported both for T and C. But the number of official residents skyrocketed for T, making the crime rate decline (just mechanical measurement prob). Note there were likely also new arrivals -&gt; need a sample of treated and controls already in Italy before the EU enlargement = those in jail at the time of the indulto, will they recidivate less? = Indulto was a brilliant trick.</p> <p>(II) Now, you cannot simply compare crime rates of legal and illegal migrants: Illegal immigrants face a higher probability of incarceration for the same offense. BUT No issue of differential treatment legal and illegal in this special case: with indulto both go back to jail for sure.</p>
METHODOLOGY	<p><b>Difference-in-Differences (DiD)</b> using two shocks:</p> <ol style="list-style-type: none"> <li>1. <b>EU Enlargement (2007)</b>: Romanians/Bulgarians granted full legal residence/work rights → treated group.</li> <li>2. <b>Mass clemency (Aug 2006)</b>: released large number of prison inmates (incl. foreigners), tracked over time → enables analysis of <b>recidivism</b> pre/post-legalization.</li> </ol> <p><b>Control group</b>: Prisoners from EU candidate countries (e.g. Albania, Serbia, Turkey) who remained illegal.</p> <p>Need: Pardoned inmates from both groups are comparable in baseline characteristics and incarceration likelihood post-recidivism. --&gt; Using propensity score weighting, covariates are balanced between groups.</p>
MAIN FINDING	Legal status causes ~50% reduction in recidivism for <b>economic crimes</b> .
EFFECT HETEROGENEITY	<ul style="list-style-type: none"> <li>- <b>Economic crimes</b>: large effect</li> <li>- <b>Violent crimes</b>: no effect</li> <li>- <b>North Italy</b>: stronger drop in recidivism (more formal labor market). Legal status improves access to formal labor markets. North has more formal jobs = higher returns to legality → stronger deterrent effect.</li> </ul>
MECHANISM	Mechanism. Legal status improves outside options (formal employment, integration), increasing opportunity cost of crime.
EXTERNAL VALIDITY	Sample: male ex-convicts from Eastern Europe. May not generalize to women, other nationalities, or contexts with different enforcement.
POLICY IMPLICATIONS	<ul style="list-style-type: none"> <li>- Causal evidence: legalization reduces crime among previously undocumented immigrants.</li> <li>- Suggests potential gains from regularization policies—but also highlights risk of selection effects and unintended incentives for future inflows.</li> </ul>

“Clicking on Heaven’s Door: The Effect of Immigrant Legalization on Crime”, Pinotti (2017)

COMPONENT	DETAILS
-----------	---------

RESEARCH QUESTION	What is the <b>causal effect</b> of <b>legalization</b> on <b>immigrant crime</b> in Italy?
TREATMENT	Obtaining a <b>residence permit</b> on click days in Dec 2007 (legalization).
ASSIGNMENT VARIABLE	<b>Application timestamp</b> (in milliseconds, example permits end after 8 minutes and 27 seconds, you have data for each municipality). Cutoff = moment quotas are filled. Tight rationing of residence permits relative to applications. You compare applicants just above to applicants just below the cutoff. Clearly you could not compare the first applicants to apply with the ones applying 2 hours later (selection bias)
SAMPLE	~110,000 <b>male applicants</b> (2007), observed 1 year <b>before and after</b> application. Matched to full police-records of serious crimes (2007–2008).
IDENTIFICATION STRATEGY	Around the cutoff: Fuzzy Regression Discontinuity Design (RD) using click day applications for residence permits (processed on a first-come, first-served basis). First stage: probability of obtaining legal status * <sup>1</sup> . This is not discrete 0 to 1. There is some ‘partial’ compliance.
	
BALANCE	Covariates are balanced around the cutoff
FIRST STAGE	Probability of being legalized jumps by ~46% at cutoff.
OUTCOME	Indicator for committing a <b>serious crime</b> in Italy (e.g., theft, robbery, drug trafficking, homicide) in 2008.
MAIN RESULT	Legalization <b>reduces crime rate by 0.6 pp</b> (from 1.1% baseline, i.e., -55%). Note how similar this result is to the Bulgaria paper! Note how one of the strengths of the paper is the fact he has crime rate pre click day!
	
EFFECT HETEROGENEITY	<ul style="list-style-type: none"> <li>- <b>Type-A (domestic worker) applicants:</b> strong crime drop (-1.3 pp)</li> <li>- <b>Type-B (firm-sponsored):</b> no effect.</li> <li>- Type-A: likely unemployed/fake job offers (why?*<sup>2</sup>) → low opportunity cost of crime → responsive to legalization.</li> <li>- Type-B: already employed → less responsive.</li> </ul>
ROBUSTNESS	<ul style="list-style-type: none"> <li>- Different Polynomial Orders (0-6)</li> <li>- McCrary Test</li> <li>- Placebo Tests (away from the true cutoff)</li> </ul>
EXTERNAL VALIDITY	Applies to <b>undocumented males</b> seeking regularization through <b>click-day quotas</b> .
POLICY RELEVANCE	Legalization of immigrants <b>reduces economically-motivated crime</b> among marginal individuals lacking legal job access.

\*<sup>1</sup> Due to rejected pre-cutoff applications (e.g., incomplete, fraudulent), some post-cutoff applications get processed retroactively. So is not manipulation but ‘fuzziness’ = perfect in our context ☺

\*<sup>2</sup> why? Imagine you are illegal. You can sponsor someone saying he is employed at my house -> A lot of illegal immigrants were sponsored as house workers. Those type A are not babysitters. They are young male unemployed. Anecdotal evidence:

- 75% of the applications [for housekeepers] were presented by other immigrants» (Corriere della Sera, 1 February 2011)

- “One out of three immigrants [...] wants the housekeeper
- Ministry of Interior (2009). “In 21% of cases the foreign applicant employer and the requested worker had the same family name”

*Comparison of click day applications vs ISMU survey*

employed as a domestic worker:	all	males	females
ISMU (only Lombardy)	0.181	0.025	0.431
Click Day, all regions	0.562	0.409	0.829
Click Day, only Lombardy	0.589	0.461	0.844

*Remark: The ISMU survey is an annual, representative survey of immigrants in Lombardy (Italy), including both regular and irregular migrants. It collects detailed data on demographics, employment, and legal status using network-based sampling for undocumented individuals.*

## CHAPTER 10: CORRUPTION

High costs of corruption (often buildings collapse) and many hidden losses (ex. Covid)

Difficulties in measurement: «Victimless» crime: the victim of corruption is the society as a whole => no single citizen has incentives to take action (common pool problem).

Difficulties to find causal impact: Spread of corruption depends on societal attitudes, values, Beliefs -> all factors that could affect the outcomes of corruption (e.g., economic development, public sector efficiency, etc.)

Some ways to measure corruption:

- Judicial evidence
- Perceptions
- Indirect evidence based on statistical anomalies («forensic econometrics»): eg political connections and missing expenditures

### A. JUDICIAL DATA NOT APPROPRIATE:

- You expect **more corruption reporting where people are very honest**, there is low tolerance.. so there is higher reporting where corruption is more pervasive.
- Very **hard to compare across countries** (different definitions of corruption, different levels of under-reporting, enforcement....). Example: firms' donations and lobbying are legal in the US, while they are illegal in many other countries.
- **Hard to compare also within the same country over time:** reported crimes often reflect anti-corruption efforts more than corruption itself. Ex. Italy: spike from 1992+ (Tangentopoli), no corruption with DC? Tangentopoli: judges + citizens decided to fight corruption. Country was so corrupt nobody wanted to go after corruption.

### B. CORRUPTION PERCEPTION INDEXES:

1. Transparency international
  - Corruption perception index: expert survey, since 1995
  - Global corruption barometer: public opinion survey about corruption in several areas (politics, justice system, police, NGOs, etc.), since 2003. Corruption barometer includes question about direct experiences of corruption («were you asked a bribe...?»).
2. World Bank, Worldwide Governance Indicators, since 1996
  - Control of corruption: expert survey
  - other measures about Rule of Law, Government Effectiveness, etc.

Problems with perception-based measures:

- subjective
- stereotypes
- reference-group dependance (Italy is bad if compared to eu)
- anti-corruption enforcement (eg a big investigation) may increase perceptions of corruption. Exactly when they start fighting it the score increases.

Expert surveys are typically well aligned, perceptions from general public are very unrelated, but perception on direct experience is more aligned to expert surveys

**C. STATISTICAL ANOMALIES (SUMO):** even though illicit behavior may remain hidden from enforcement authorities, they often leave a «statistical trace» in aggregate data.

#### C1. Ex political connections

##### **Fisman (2001) – Estimating the Value of Political Connections**

**Political connection (eg mediaset):** a firm is considered politically connected if it has close ties to high-ranking politicians / to a party.

SECTION	DETAILS
<b>MOTIVATION</b>	<ul style="list-style-type: none"> <li>- Focus: Indonesia's 1997 crisis and investor panic. Suharto: ruling Indonesia for 3 decades, many children with positions in power in many companies.</li> <li>- Hypothesis: Firm value driven by political ties (to Suharto), not productivity.</li> <li>- Aim: Quantify how much firm value depends on political connections.</li> </ul>
<b>RESEARCH QUESTION</b>	How much do political connections contribute to firm value in an emerging economy?
<b>LITERATURE REVIEW</b>	<ul style="list-style-type: none"> <li>- <b>Roberts (1990):</b> U.S. senator's death; small firm-level effects from political ties.</li> <li>- Fisman advances by using stronger measures of connectedness and multiple natural events.</li> </ul>
<b>BACKGROUND</b>	The Suharto family has vast connections to business groups. Actually: «Suharto's dependency index» (POL) elaborated by a consulting firm in Jakarta to help foreign investors classify Indonesian groups on a 1-5 scale according to their proximity to Suharto's family
<b>DATA</b>	<ol style="list-style-type: none"> <li>1. <b>Accounting &amp; Stock Data</b> <ul style="list-style-type: none"> <li>• Source: Extel Financials (1995), Investamatic (for missing prices).</li> </ul> </li> <li>2. <b>Political Connectedness</b> <ul style="list-style-type: none"> <li>• Suharto Dependency Index (Castle Group, 1995), 1-5 scale for 25 largest groups.</li> <li>• 79 firms total, including firms linked to Suharto's children (score = 5).</li> </ul> </li> </ol>
<b>METHODOLOGY</b>	<p><b>Event Study Design</b></p> <p>Rumors about Suharto's health during the period 1995-1997 (Six major rumor episodes) -&gt; compare the stock market return of</p> <ul style="list-style-type: none"> <li>- connected vs. non-connected firms</li> <li>- during periods of rumors vs. "normal times"</li> </ul>
<b>KEY FINDINGS</b>	<ul style="list-style-type: none"> <li>- In every event, more politically connected firms experienced larger losses.</li> <li>- Interaction term is positive and significant → stronger negative reaction when rumors are more severe.</li> </ul>
<b>ROBUSTNESS CHECKS</b>	<ul style="list-style-type: none"> <li>- <b>Market Sensitivity:</b> No correlation between POL and price drops from unrelated bad news (e.g., global market shocks). Checks whether POL is also correlated with returns on other major events, e.g., exchange rate collapse.</li> <li>- <b>Event Window:</b> Results robust when using <math>\pm 1</math> or <math>\pm 2</math> day windows.</li> <li>- <b>Linearity of POL:</b> Monotonic and consistent; flexible specification confirms results. Tests if returns decrease monotonically with POL (0 to 4)</li> </ul>
<b>CONCLUSION</b>	<ul style="list-style-type: none"> <li>- Political connections significantly drive firm value.</li> <li>- Applicable to other corrupt countries; Indonesia not even most corrupt.</li> <li>- Suggests major macroeconomic distortions from rent-seeking.</li> </ul>

#### C2. Ex Missing Expenditures

Statistical anomaly 2: Missing expenditures (if there is a corruption similar stuff costs more)

- Idea: corruption should increase costs of goods and services -> measure excess expenditure in public procurement for given quantity of physical infrastructure
- Golden & Picci (2005): cost of public infrastructures across Italian regions, taking into account differences in terrain characteristics.
- *Monitoring corruption: evidence from a field experiment in Indonesia A. Olken (2007):* studies over 600 Indonesian village road projects using a randomized field experiment. Increasing top-down government audits significantly reduced corruption (measured as missing expenditures). Missing expenditures = official project cost – estimated project cost. Estimated by Independent engineers covertly re-estimated road costs (samples of the street and measuring how much water is there) using physical audits. Measured costs keeping constant the quality.

## D. EVENT STUDY

Why studying corruption in Brazil:

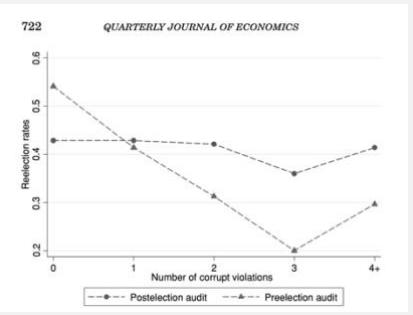
- Corruption is widespread
- Rich registry data covering the entire population
- Interesting policy experiments

Data

- Registries of national-level and local politicians
- Family linkages (tax records)
- Tax records & income data, matched employer-employee data
- Judicial records

**Ferraz & Finan (2008) — Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes**

COMPONENT	SUMMARY
<b>RESEARCH QUESTION</b>	Does <b>public disclosure of municipal corruption</b> affect incumbent electoral performance?
<b>SETTING</b>	Brazil, municipal elections, 2004.
<b>IDEAL EXPERIMENT</b>	Ideal Experiment: audit municipalities to record their corruption levels and then releasing this information to voters in a random subset of municipalities (treated municipality). For any given level of corruption, one would then perform a simple comparison of the electoral outcomes in Treated municipalities.
<b>NATURAL EXPERIMENT</b>	<p><b>Natural Experiment (perfect):</b> In 2003 Brazil's federal Gov launched an anti-corruption program. <b>Brazil randomly audited municipalities (&lt;450,000 pop.) and publicly disclosed findings.</b> Auditors <u>examine accounts and documents to detect fraud in procurement</u>. The auditors describe the irregularity found and assign a code that classify irregularities</p> <ul style="list-style-type: none"> <li>• Corruption: number of irregularities classified as either moderate or severe irregularities</li> <li>• Mismanagement: number the irregularities associated with administrative irregularities</li> </ul> <p>KEY: Exploits <b>random timing</b> of audits around 2004 election → compares municipalities audited before vs after the election. <u>Because municipalities were selected at random, the set of municipalities whose audit reports were only made available after the elections represent a valid control group.</u> 168 municipalities were audited after the election (Control group), whereas 205 municipalities that were audited before the election (treatment group). We have corruption levels for two groups of municipalities: those whose corruption levels were released prior to the elections—potentially affecting voters' perceptions of the mayor's corruptness—and those that were audited and had their results released only after.</p> <p><u>Remark: You take the control from the program because you can control for the corruption level!!</u></p> <p>*Recall that for the estimation we have to restrict our sample to only first- term mayors, who are eligible for reelection</p>
<b>DATA</b>	- 373 municipalities with first-term mayors eligible for re-election. - Audit data: CGU corruption reports (coded by authors). - Election data: TSE (2000, 2004). - Municipal controls: IBGE census + administrative surveys.
<b>OUTCOME VARIABLE</b>	<b>Re-election of incumbent mayor.</b>
<b>HETEROGENEITY: CORRUPTION LEVEL</b>	Ams: municipalities audited before election Cms: number of corrupt violations. Mms: presence of the local radio  The triple interaction will represent: municipalities audited before election bs non audited municipalities, given the level of corruption and the presence of radio station.

<b>KEY FINDINGS</b>	<ul style="list-style-type: none"> <li>- <b>No avg. effect</b> of audit on re-election when corruption is not accounted for. This makes sense, The effects of the audits are likely to depend on both the type of information revealed and the presence of local media (you are averaging heterogenous treatment effects)</li> </ul>																		
	<ul style="list-style-type: none"> <li>- <b>Strong effect conditional on corruption level:</b> <ul style="list-style-type: none"> <li>• 2 corruption violations → 7 pp ↓ in re-election.</li> <li>• 3 violations → 14 pp ↓.</li> </ul> </li> <li>- <b>Radio amplifies effect:</b> <ul style="list-style-type: none"> <li>• Audit in municipality with local radio &amp; 2 violations → 11 pp ↓.</li> <li>• If 0 violations → audit <b>increased</b> re-election (17 pp ↑).</li> </ul> </li> </ul>																		
<b>MECHANISM</b>	<p>Heterogeneity due to updating beliefs!</p>  <table border="1"> <caption>Data extracted from the graph</caption> <thead> <tr> <th>Number of corrupt violations</th> <th>Postselection audit (Relection rates)</th> <th>Preelection audit (Relection rates)</th> </tr> </thead> <tbody> <tr> <td>0</td> <td>0.55</td> <td>0.65</td> </tr> <tr> <td>1</td> <td>0.55</td> <td>0.45</td> </tr> <tr> <td>2</td> <td>0.55</td> <td>0.35</td> </tr> <tr> <td>3</td> <td>0.35</td> <td>0.20</td> </tr> <tr> <td>4+</td> <td>0.40</td> <td>0.20</td> </tr> </tbody> </table> <ul style="list-style-type: none"> <li>- At corruption levels of less than one (which is the sample median), voters' prior beliefs appear to have overestimated the incumbent's corruption level, and the audits have increased an incumbent's likelihood of reelection.</li> <li>- Beyond this crossover point, politicians are punished, as voters have systematically underestimated their corruption levels.</li> </ul>	Number of corrupt violations	Postselection audit (Relection rates)	Preelection audit (Relection rates)	0	0.55	0.65	1	0.55	0.45	2	0.55	0.35	3	0.35	0.20	4+	0.40	0.20
Number of corrupt violations	Postselection audit (Relection rates)	Preelection audit (Relection rates)																	
0	0.55	0.65																	
1	0.55	0.45																	
2	0.55	0.35																	
3	0.35	0.20																	
4+	0.40	0.20																	
<b>ROBUSTNESS CHECKS</b>	<ul style="list-style-type: none"> <li>- Balance checks confirm random audit timing (municipalities audited pre and post-election are similar)</li> <li>- Audit quality consistent pre/post-election.</li> <li>- Regression results include controls for education, population size, mayor's party, municipality income, etc.</li> <li>- Used different proxies for media exposure: % of households with radio, Newspaper presence, TV station presence</li> </ul>																		
<b>POLICY IMPLICATIONS</b>	<ul style="list-style-type: none"> <li>- Transparency + independent audits improve political accountability.</li> <li>- Media access is crucial to empower voters.</li> </ul>																		

Colonnelli & Prem (2022), "Corruption and Firms", Review of Economic Studies

CATEGORY	DETAILS
<b>RESEARCH QUESTION</b>	What are the real economic effects of anti-corruption audits on local firms?
<b>SETTING</b>	Brazil, 2003–2014; randomized municipal audits by CGU (federal audit office).
<b>METHODOLOGY</b>	<ul style="list-style-type: none"> <li>- <b>Staggered Difference-in-Differences</b> using random audit timing.</li> <li>- <b>Event-study:</b> treated vs never/audited-later municipalities.</li> <li>- Audit assignment via public lottery ensures exogeneity.</li> </ul>
<b>MAIN DATA</b>	<ul style="list-style-type: none"> <li>- RAIS (matched employer-employee census): For each employee we have education, gender, wage, hiring and firing, occupational codes, contract details, nationality, age, hours working, and education. We aggregate the measures at the establishment, firm, and municipality level.</li> <li>- PAC and PAS surveys - financial information on sales and investment.</li> <li>- Election, campaign contribution, and political connection data.</li> <li>- Public procurement data</li> </ul>
<b>MAIN OUTCOMES</b>	<ul style="list-style-type: none"> <li>- # firms, # of establishments, total sales, deposits</li> </ul>

<b>KEY RESULTS</b>	<ul style="list-style-type: none"> <li>+0.9% N. of establishments 3 years post-audit.</li> </ul>
<b>MECHANISMS</b>	<ul style="list-style-type: none"> <li>+6% sales; +3% bank deposits</li> </ul>
<b>SPILLOVERS</b>	<p>1. <b>Detection:</b> audits lead to removal of corrupt officials.</p> <p>2. <b>Misallocation:</b> On the other hand, politically connected firms, such as campaign donors or firms whose manager is an elected politician, shrink considerably; efficient entrants grow.</p>
<b>HETEROGENEITY</b>	<p>Nearby (non-audited) municipalities react via fear of audits → +1.2% firm growth. We uncover the presence of large spillover effects [...] a nearby audit has an impact on non-audited municipalities that is similar in magnitudes to our baseline effects, i.e., a 1.2% increase in the number of firms.</p> <ul style="list-style-type: none"> <li><b>Stronger effects</b> where audits actually detect corruption.</li> <li><b>Politically connected firms, such as campaign donors or firms whose manager is an elected politician, shrink considerably</b></li> <li>Effects <b>fully concentrated in Gov-dependent sectors</b> only (+1.4%). Auditors identified many irregularities in bribes in public procurement. As a result, we expect to find effects on sectors with higher government dependence (highly connected to government procurement, or sectors where irregularities were concentrated (more exposed to exposure to local corruption), strong overlap).</li> <li><b>No effect on other sectors.</b></li> </ul>
<b>THEORY CONTRIBUTION</b>	<ul style="list-style-type: none"> <li>Rejects "efficient corruption" (i.e., corruption as grease).</li> <li>Supports "corruption as tax" on firm entry and efficiency.</li> </ul>
<b>ROBUSTNESS CHECKS</b>	<ul style="list-style-type: none"> <li>Parallel pre-trends.</li> <li>No changes in federal transfers, informal/formal sector shifts explain the results.</li> </ul>
<b>POLICY IMPLICATIONS</b>	<p>Anti-corruption audits → substantial local economic gains.</p>

Very similar to council dismissal paper in Italy

**Family matters Politics and jobs in Brazil, Barreto, Britto, Fonseca, Pinotti, Sampaio <- not included?**

Corruption is misuse of public office for private gains

Politicians can extract private gains in several ways

- Ask for bribes
- Steal public funds
- Distort policies and regulations to their own benefit
- Nepotism: enhance the employment opportunities of their family members (Nepotism)

**Idea: Quantify the benefits of having a relative in municipal councils.**

**Context:** In municipal governments employed 11.4 million people + Mayors have high discretion in hiring, particularly those in senior positions & temporary jobs

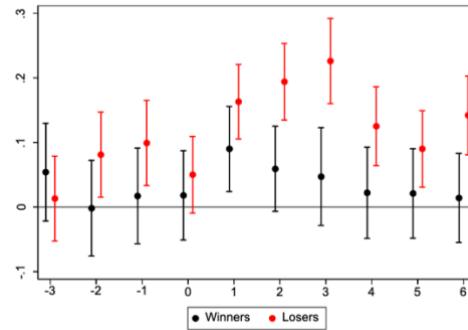
Heterogeneity: Public vs private earnings, majors vs councilors, councilors of opposition vs councilors of winning party.

Methodology: Regression Discontinuity Design

- Mayoral candidate obtaining one vote more than the other(s) is appointed → compare candidates appointed/non-appointed by a narrow margin (as-good-as-randomly assigned to winning the elections), clearly you want to compare very similar politicians (popularity & a mixture of other traits). First used by David Lee 2008 (Estimate the incumbency advantage: does winning one election increase the chance of winning the next?).

Results: Relatives of elected politicians shift from private to public sector jobs

- increase in total income for the family of the mayor, driven by strong increase in public earnings offsetting a decrease in private earnings. Effect on mayor's family > effect on councilors' family
- increase in total income for the family of councilors of the same party, driven by strong increase in public earnings offsetting a decrease in private
- increase in total income for the family of councilors of the minority party, driven by strong increase in public earnings offsetting a decrease in private! Effect larger than for councilors of the winning party!



Mechanism: mayors in Brazil are supported by minority government. Nepotism is a tool for political bargaining = Benefits for councilors of opposition parties.

#### Increase in earnings depending on MV of mayoral candidate

- No rents for councilors when the mayor is appointed with a large majority
- Larger rents for opposition councilors and for independents

All	Margin of victory				Independents
	< -20%	[-20%, 0%]	[0%, +20%]	> +20%	
0.117*** (0.018)	0.147*** (0.043)	0.132*** (0.034)	0.085** (0.035)	-0.049 (0.045)	0.238*** (0.060)

Effect of the Anti-nepotism decision by Brazil's Supreme Court (2008): ruled that it is unconstitutional to discretionally appoint family members in all branches (executive, legislative, and judiciary) of governments at all levels (municipality, state, and national). Reduction in all we have seen above!

## CHAPTER 11: DRUGS

Drugs: chemical substances inducing physiological or psychological effects (eg stimulants, depressants, antidepressants, anxiolytics, antipsychotics, hallucinogens).

Total drug consumption has risen to 271 millions (+30% since 2009). The most widely diffused drug is cannabis (188 mln users in the world).

Some drugs can be used for medication -> pharmaceutical drugs

Others are recreational drugs:

- «heavy»: opioids, cocaine, synthetic drugs
- «light»: marijuana/cannabis, nicotine, caffeine
- alcohol (unclear whether heavy or light)

Both pharmaceutical and recreational drugs are possibly addictive and have severe side effects

Drug policy faces a key trade-off between liberalization and paternalism.

- Liberalizing—through legalization or decriminalization— aims to weaken mafias by cutting their profits, reducing violence between criminal groups and with the state. It also saves enforcement costs and can generate tax revenue. Control quality maybe reducing health risks from consumption.
- However, liberalization may increase drug availability and use, raising public health concerns. Paternalism, by keeping drugs illegal, seeks to protect individuals from harm.

Marijuana: obtained from Cannabis, both pharmaceutical and recreational use. recreational use still illicit in most countries, but wave of decriminalization in recent years

Europe: traditionally legal in the Netherlands, recent decriminalization in Portugal, Czech Republic, Norway, etc.

outside Europe: Uruguay was the first state to fully legalize marijuana

Recent wave of regularization / decriminalization motivated by a cost benefit analysis cost > benefits. Shift in public opinion towards legalization.

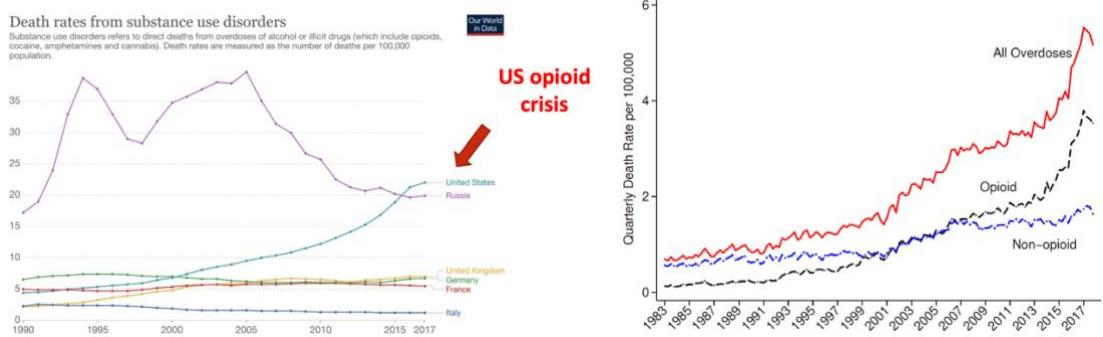
Best solution: RCT, cannabis to some ppl vs controls. Ethically unfeasible. But some medical studies did. Limited interest (reflexes, higher reaction time etc). conclusion: “THC impairs performance on high-level cognitive functions essential for goal-directed behavior”

### *Marie & Zöllitz (2017) — High Achievers? Cannabis Access and Academic Performance*

<i>Component</i>	<i>Summary</i>
<b>Research Question</b>	Does legal access to cannabis affect university students' academic performance?
<b>Context</b>	Maastricht is a border city close to Bel and Ger. It has both a large student population and lots of drug tourism from the rest of Europe.
<b>Natural Experiment</b>	Maastricht, Netherlands. In 2011 Oct 1 <sup>st</sup> , cannabis shops restricted access based on nationality (Dutch, German, Belgian allowed; others banned). The policy aimed at reducing drug tourism, not targeting students specifically.

<b>Identification Strategy</b>	<b>Difference-in-differences:</b> compares course grades of affected (non-DGB) vs. unaffected (DGB: Dutch, German, Belgian) students before and during the ban. Uses administrative student-level panel data with individual fixed effects. Some imperfect compliance (German guy buys for Italian friend + illegal market), your effect will be a lower bound. Estimating the Intention to ban people. Cannot effect true treatment effect, we need to know exact compliance. What if they started consuming more Alcohol?
	VERY NICE FIGURE IN SLIDES, GREEN, YELLOW, RED
<b>Data</b>	<ul style="list-style-type: none"> <li>- data on all students taking bachelor courses in economics over 3 academic years (2009/10 to 2011/12). 58,000 course grades for 4,800 students: <b>53% German, 33% Dutch, 4% Belgian &amp; 10% Non-DGB (Spanish, Italian etc)</b></li> <li>- 57,000+ course-grade records.</li> <li>- Course evaluations.</li> <li>- Nationality, age, gender.</li> </ul>
<b>Issues</b>	<ul style="list-style-type: none"> <li>- No data on smoking behavior (compliance with treatment assignment) =&gt; ITT. Should still scale up for the actual difference in smoking behavior.</li> <li>- In practice: non-DGB could probably access marijuana, but at increased cost</li> </ul>
<b>Key Findings</b>	<ul style="list-style-type: none"> <li>- Restricting cannabis access <math>\uparrow</math> <b>grades by 0.11 SD</b> and <math>\uparrow</math> <b>pass rate by 5.4%</b>.</li> <li>- No change in dropout rates.</li> <li>- Effects larger for <b>numerical courses</b> (<math>3.5 \times</math> bigger effect, math stats).</li> <li>- Stronger effects for <b>women, younger, and low-performing</b> students.</li> </ul>
<b>Mechanism</b>	Improved cognitive performance (esp. numeracy), not due to increased study effort: course evaluations show $\uparrow$ <b>understanding</b> but <b>no change in hours worked</b> .
<b>Spillovers</b>	Slight peer effect: higher share of affected students in class $\uparrow$ <b>pass rates</b> for treated students. No effect from teachers' cannabis access.
<b>Robustness Checks</b>	<ul style="list-style-type: none"> <li>- Time/placebo tests (fake policy period, fake treatment group).</li> <li>- Pre-trend balance.</li> </ul>
<b>Policy Implications</b>	First causal evidence that a change in access to "light" drugs can have immediate impact on cognitive skills. Drug policy can impact human capital accumulation; effects are <b>heterogeneous</b> across subgroups. This is just Short run effect, would be interesting to see LR effect.

Focus now on heavy drugs! in 2017, almost 600k deaths from drug use (+134% in the last 30 years): US and Russia the two nations most affected. Russia has displayed very high rates at least since the fall of URSS; while the US has had an astonishing increase in the last two decades due to the opioid crisis. Stunning numbers: In San Francisco Drug addicts outnumber high school students, highlighting the scale of addiction even in major urban centers.



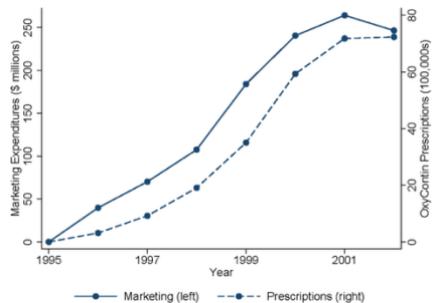
Remark: drug deaths are extremely higher (x10) in high income countries.

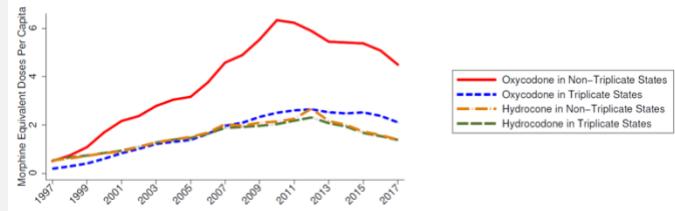
Opioids comprise

- natural opiates (e.g., heroin, morphine)
- synthetic drugs derived from opium, including prescription painkillers (Vicodin and OxyContin) and non-prescription illicit drugs (Fentanyl).

*Alpert et al. (2019) — Origins of the Opioid Crisis and Its Enduring Impacts:*

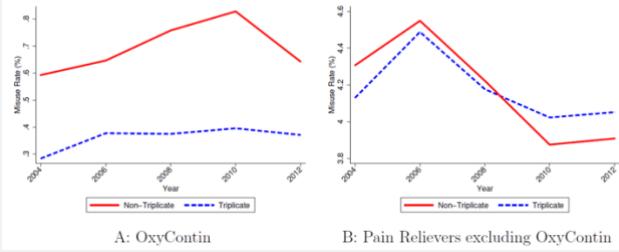
<i>Component</i>	<i>Summary</i>
<b>Research Question</b>  <b>Context &amp; Setting</b>  <b>Identification Strategy</b>	<p><b>What role did the 1996 introduction and marketing of OxyContin play in initiating and sustaining the U.S. opioid crisis?</b></p> <p>- In 1996 Purdue pharma introduced OxyContin, a prescription used for the treatment of chronic pain (e.g., from cancer or other terminal illness)  - extended-release formula, but it could be crushed for inhalation/injection -&gt; abuse and addiction  - very aggressive marketing (and gifts to physicians), revenues increased from \$48 mils in 1996 to \$3.1 billions in 2010, focus was diffusing the pharma also for treatment of non cancer related pain.</p> <p>- 2010: replaced by abuse-deterrent version that could not be crushed</p> <p>- the role of triplicate prescriptions: stringent monitoring of prescriptions required in some states for several opioids, including OxyContin. Three copies of prescription: one for the physician, one for the pharmacy, and one for the drug monitoring agency =&gt; monitoring of abnormal number of prescriptions by a single physician ("triplicate states" in 1996: CA, ID, IL, NY, TX)  - Purdue Pharma saw triplicate prescriptions as a significant barrier to the marketing of OxyContin. Internal docs: "<i>The physicians in the triplicate state did not respond positively to the drug, since it is a Class II narcotic which would require triplicate prescriptions.</i>"  - Purdue invested less in marketing in such regions and made less gifts to physicians. This affected the state level exposure specifically to oxycotin! See image:  * distribution of hydrocodone (not subject to specific prescriptions) presents no differences!</p>





- U.S., 1996 onward; exploiting cross-state variation in exposure to OxyContin based on pre-existing triplicate prescription programs that limited opioid prescribing and marketing.

#### □ OxyContin abuses (non-medical uses)



- Difference-in-differences using variation in exposure: **triplicate states** (more regulation) vs. **non-triplicate states** (less regulation). Event studies complement analysis.

#### Data

- Overdose deaths: CDC vital statistics (1991–2017).
- OxyContin distribution: ARCOS DEA
- Medicaid prescription data (1996–2005).
- Covariates: CPS (Current population survey)

#### Main Outcomes

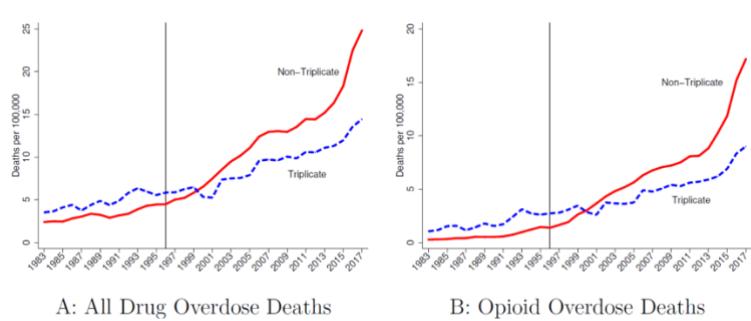
Drug overdose deaths (all and opioid-specific), prescription and misuse rates.

#### Empirical Model

Panel regressions: death rate per 100,000 = state + year FE + (triplicate  $\times$  post indicators) + controls. Event studies show dynamic effects around OxyContin's launch (normalized to zero pre-1996).

#### Key Findings

- **Exposure effect:** Non-triplicate states saw  $>2\times$  OxyContin distribution and higher overdose growth.
- Triplicate states had higher overdose rates pre-1996, but the trend reversed post-OxyContin.
- **Magnitude:**  $\sim 36\%$  fewer deaths if triplicate.  $45\%$  less opioid



#### Heterogeneity

- Early effects: deaths driven by prescription opioids.
- Post-2010: sharp rise in heroin/fentanyl deaths, especially in initially exposed states (transition to illicit opioids as prescriptions become less available.)

Two channels: (1) marketing, (2) preexisting regulation

#### Robustness Checks

- Falsify treatment in: 1) Pre-1996 years, 2) Non-opioid mortality outcomes
- Permutation Test. randomly assign triplicate status to five nontriplicate states and then estimate placebo effects for three postperiods.
- Controls for state policies (PDMPs, Pill Mill Laws etc ).
- Similar pretrends 1996. First, we use a synthetic control approach to account for systematic differences in pretreatment outcomes.

<b>Policy Implications</b>	<ul style="list-style-type: none"> <li>- Initial policy constraints (triplicate programs) had <b>long-term protective effects</b>.</li> <li>- Pharmaceutical marketing can have <b>persistent public health consequences</b>.</li> <li>- Early regulation shapes epidemic trajectories.</li> </ul>
----------------------------	--

Eichmeyer & Zhang (2022) — *Pathways into Opioid Dependence: Evidence from Practice Variation in Emergency Departments*:

<i>Component</i>	<i>Summary</i>
<b>Research Question</b>	Does receiving an opioid prescription in the emergency department (ED) causally increase long-term opioid use, misuse, and adverse outcomes?
<b>Context &amp; Setting</b>	U.S. Veterans Health Administration (VHA), 2006–2016. Focus: ~2 million veterans with ED visits, leveraging physician-level variation in opioid prescribing practices (The physician leniency variable is a leave-one-out, residualized average prescribing rate that fully adjusts for patient case-mix and contextual factors, isolating the doctor's own prescribing tendency).
<b>Identification Strategy</b>	Exploits quasi-random assignment of patients to ED physicians with varying opioid prescribing leniency (similar to a “judge design”). Uses IV: physician leniency → opioid prescription → outcomes.
<b>Data</b>	<ul style="list-style-type: none"> <li>- VHA health records (ED, pharmacy, diagnosis data for veterans).</li> <li>- Medicare, Medicaid claims.</li> <li>- CDC National Death Index.</li> <li>- Detailed opioid prescription &amp; outcome measures.</li> </ul>
<b>Sample</b>	<ul style="list-style-type: none"> <li>- Veterans' first ED visit</li> <li>- Conditions prescribed opioids ≥10% of the time</li> <li>- Exclude high prior opioid users, terminally ill, and rare prescribers.</li> </ul>
<b>Empirical Model</b>	<p>2SLS: Instrument = physician prescribing leniency.</p> <ul style="list-style-type: none"> <li>- Long-term opioid use (180+ day supply in 12m)</li> <li>- Opioid-seeking behavior</li> <li>- Opioid Use Disorder (OUD)</li> <li>- Opioid overdose mortality</li> </ul> <p>Controls: detailed patient, physician, diagnosis-level covariates.</p>
<b>Key Findings</b>	<ul style="list-style-type: none"> <li>- ED opioid prescription ↑ long-term use by 1.2 pp (20% ↑).</li> <li>- ↑ Opioid-seeking behavior by 2.5 pp (17% ↑).</li> <li>- ↑ OUD by 0.34 pp (10% ↑).</li> <li>- ↑ Overdose mortality by 0.075 pp (45% ↑).</li> <li>- Effects persist for ≥24 months.</li> <li>- No pain improvement</li> </ul>
<b>Mechanism</b>	Prescription opioids initiate sustained use and misuse pathways. Placebo tests confirm results stem from opioid exposure, not other physician behaviors.
<b>Robustness Checks</b>	<ul style="list-style-type: none"> <li>- Placebo: no effect for conditions rarely prescribed opioids.</li> <li>- Balance: Check if patients assigned to high- vs. low-opioid physicians differ in baseline characteristics.</li> </ul>
<b>Policy Implications</b>	<ul style="list-style-type: none"> <li>- Even a single ED opioid prescription can cause long-term harm.</li> <li>- Guidelines limiting opioid prescribing (especially in acute care) are crucial.</li> <li>- Pain relief benefits do not outweigh addiction/overdose risks in this population.</li> </ul>

Exogeneity drug users are different than others, ex. drink a lot, than control. Then you maybe are finding the joint effect of drug + drinking.

Underreporting: Issue: people don't want to tell to doctor etc.

## CHAPTER 12: DRUG CRACKDOWNS (what happens when you try to prevent drug trafficking)

**Background:**

- In USA, largest cause of mortality for individuals under 50 is drug overdoses. 500,000 people have died from drug overdoses in the last five years alone.
- Entire generation disappeared from the labor market.
- Drug usage is associated with other types of crime

**History:** previous waves of the “opiate crisis” lead to today’s fentanyl epidemic

- i. It all began with the overprescribing of opioid medications, especially OxyContin; This led to a spike in opioid overdoses;
- ii. As the crisis worsened, policymakers tried to crack down on prescription opioids, implementing regulations to make them harder to obtain and abuse;
- iii. Instead of solving the problem, this shift fueled a surge in heroin
- iv. Efforts came to stop the heroin trade, particularly from Mexico
- v. Fentanyl started to be used, U.S. law enforcement arrested El Chapo’s son in an effort to disrupt the fentanyl trade.
- v. Fentanyl prices surged, and then Chinese suppliers flooded the market with a new substance—a horse tranquilizer, of all things

Every regulatory effort seems to act like a trigger, setting off the next wave of the epidemic. Failure of policy. See the graph plateau and increases. **“People need what they need, and they’ll find a way to get it”. If you want to truly reduce demand, you need to understand substitution, anticipate market reactions, and build policy holistically—not one drug at a time.**

#### **How to address the issue? The public health approach is ineffective!**

- The idea is to reduce harm, to make drug use less deadly rather than trying (and failing) to eliminate it altogether.
  - **Harm reduction policies lead to moral hazard** (when you reduce the risks of a dangerous behavior, people might just do more of it)
    - Ex. The opening of syringe exchange programs led to increased overdose mortality. Syringe exchange programs is straightforward: The goal is to prevent people from sharing needles or picking them up off the street. Give people clean needles, and you reduce the transmission of diseases like HIV and hepatitis, which are huge public health burdens. This seems a great policy. But IN PRACTICE when you lower the cost of using drugs—by making it safer and easier—usage often goes up! That’s the moral hazard.
    - Ex. same for safe injection sites
    - Ex. Naloxone access laws led to increased hospital admissions for overdoses. Another example is Naloxone, or Narcan, a drug that can reverse opioid overdoses. BUT with Naloxone widely available, the perceived risk of overdosing goes down!
- Intuition: Public health approaches reduced the effective cost of drug use → users respond to price signals.

Making drugs less risky leads people to overconsumption!

#### **How can illegal drug markets be disrupted?**

##### **A. Regulation of legal markets that support illegal drug markets (Overprescribing prescription)**

##### **B. “Up stream” law enforcement efforts to prevent illegal drugs from entering local markets (disrupt supply). Stop drugs before they reach streets: border control, seizures, targeting international trafficking networks**

##### **C. Localized enforcement efforts (raids) aimed at disrupting existing illegal markets (disrupt retail)**

**The key idea:** No matter the approach, the core logic of enforcement is always the same: you can’t completely eliminate narcotics, because you can’t magically erase demand. So the goal becomes making supply more difficult and costly, especially for sellers. In theory, this raises prices for consumers, which should then reduce demand—and with that, the negative side effects like crime, overdoses, and community decline. The issue is that drug demand doesn’t behave like typical consumer demand. You are addicted, desperate and with severe withdrawal symptoms. Demand is highly inelastic—people keep buying, no matter the cost, they will substitute. This is the painful economics of addiction. Ex. Arrests of local dealers can increase drug overdoses due to risky search behavior (Ray et al. 2023). Because the users who depended on that dealer now have to go searching for a new source in an unregulated, dangerous market. They may end up trying unfamiliar substances or using unsafe supply chains, leading to more overdoses.

**A. Regulation of legal markets that support illegal drug markets:** The idea is that we can regulate our way out of this crisis

##### **I. The War on Drugs: Methamphetamine, Public Health, and Crime. Dobkin and Nicosia (2009)**

- U.S. passed laws to restrict sale and distribution of these ingredients (previously unregulated).
- Costs to sellers increase → higher prices and lower quality etc

- Main Results (temporary):

- Decrease in hospital admissions mentioning meth
- Increase in methamphetamine treatment admissions (rehab)
- No real crime effects (thefts etc), aside from reductions in possession and sale arrests. Seems a win but...
- But—and this is key—policymakers didn't anticipate the substitution effects. Substitution Results: Increase in cocaine, opioid, and marijuana hospitalizations.

## II. Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids, Alpert et al. (2018)

- Users of OxyContin quickly realized that if you crushed the pill, it bypassed the slow-release mechanism.
- 2010 introduction of “abuse deterrent” OxyContin (digestible wax in the pill to prevent crushing, force an extended release)
- Making the pills more difficult to abuse worked. The “curve” of Oxycontin abuse was flattened.
- BUT Users substituted to lower cost heroin. Before 2010, heroin was largely viewed as a marginal drug.. The transition happened quickly and catastrophically.
- And this is when the U.S. opioid epidemic truly entered its deadliest phase. Heroin-related deaths jumped dramatically, as did the overall death toll. What began as an attempt to fix prescription opioid abuse ended up accelerating a shift to something far worse.

## III. Disrupting Drug Markets: The Effects of Crackdowns on Rogue Opioid Suppliers, Soliman (2022)

- Original “opioid crisis” was largely driven by misuse and over-prescribing of pharmaceuticals
- Law enforcement targeted specific over-prescribing doctors
- After a crackdown, opioid prescribing drops significantly and persistently in the local area
  - The supply of prescription opioids is disrupted when a high-volume prescriber is shut down
  - Change in black market price of diverted prescription opioids (logged price per milligram): Price of diverted pills rises after crackdowns, due to reduced local supply
  - BUT again, substitution and Increase in heroine overdose deaths

## **B. “Up stream” law enforcement efforts to prevent illegal drugs from entering local markets (distrust supply). Stop drugs before they reach cities: border control, seizures, targeting international trafficking networks**

### I. Opioid Use, Mortality Risks and Crime: Insights from a Rapid Reduction in Heroin Supply, Moore and Schnepel (2024)

- Increased enforcement efforts in 2000, led to a massive supply shock in 2001: Ports are tightly controlled → harder to smuggle heroine compared to land borders
- Maybe not so generalizable- pre-fentanyl so no real substitute for heroin. And most places aren’t islands.
- Identify individuals using heroin pre-2000 (from arrest records). Compare outcomes for these individuals to other arrestees using non-opioid drugs.
- Post-intervention massive increases in heroin price (4x, compared to flat / decreasing prices for cocaine and methamphetamines). But interestingly, the prices of other major drugs—what we might think of as “competitors”—don’t move much.
- Individuals initially substitute to alternative drugs = non-opiod drug use. In the short term, there’s a noticeable spike in hard drug use and possession. Users start experimenting—trying other substances in place of heroin. BUT These are completely different effects from what an opioid user is seeking. So users try these alternatives. They don’t work. Alongside this, we also see temporary increases in violent crimes: homicides, manslaughter, and robberies all go up briefly. But these spikes are short-lived!
- In the long run, persistent reduction in opioid related mortality
- It’s one of the few documented cases where a supply-side intervention worked, at least in the short to medium term: supply is seriously disrupted and alternatives are hard to access, even a deeply entrenched drug problem can be contained—at least in very specific settings!

## **C. Localized enforcement efforts (raids) aimed at disrupting existing illegal markets (distrust retail)**

### 1. The Crack Epidemic and Initial Policy Failure

In the 1980s–1990s, the U.S. faced a rapid rise in crack cocaine use, primarily affecting poor urban (often Black) communities. The federal response, especially under Reagan and Clinton, centered on a hardline “War on Drugs” strategy: heavy policing, mass arrests, and extremely harsh sentencing. Epitomized by racially motivated and otherwise indiscriminate stop-and-frisk policing. Nonviolent offenders were sentenced to decades in prison for small amounts of crack. Imagine the price tag on providing decades of healthcare and hospice care for aging inmates who were locked up for low-level drug offenses. All to stop crack—which, by the way, didn’t stop. It’s still around. This indiscriminate approach led to a 161% increase in the prison population, with drug possession arrests rising by 89% and drug sale arrests by 210%.

### 2. Rethinking Enforcement: From Blunt to Surgical

The failure of broad enforcement led to a more strategic approach: targeted enforcement based on intelligence and network analysis. A highly strategic, military-style enforcement campaign. Rather than arresting low-level dealers and users, law

enforcement now aims to disrupt drug supply chains by removing key actors—those central to distribution networks. It's not about arresting everyone—it's about cutting off the structural arteries of the drug trade. For instance, if police pressure increases on one dealer, their costs rise, pushing customers to competitors (Gen Eq dynamics). This creates a simple but frustrating outcome: law enforcement doesn't reduce drug use—it just shifts it around. If instead police target the supplier (who holds market power), the shock propagates through the network—raising prices and reducing demand across the board. If you target him, the effects cascade through the network. My costs go up too—because he's charging me more, or can't supply me at all. That means prices go up across the board, and now there's no cheaper dealer to switch to. The entire market contracts if the **HUB** is hit.

### 3. Case Study: Kensington Enforcement Campaign

A key application of this approach took place in Kensington, Philadelphia—a hotspot for open-air drug markets. After years of surveillance, wiretaps, and informants, a five-year intelligence-based operation led to the arrest of **six** high-level opioid dealers. Despite the small number of arrests, opioid prices rose sharply, and market activity—tracked via cellphone location data\*1—dropped significantly. One would expect new dealers to enter the market or existing dealers to relocate. However, importantly, surrounding areas (up to 50 km away, 2hrs of travel time) did not see an uptick in drug activity, suggesting genuine contraction rather than displacement. Overdose deaths across the metro area declined by 20–30%, and traffic into all nearby markets fell, indicating broad regional disruption. That's the kind of outcome we're always hoping for in drug policy: not redistribution, but true disruption. These markets are intrinsically linked—economically and behaviorally, by intervening in just a 1.2 square kilometer area, we see ripple effects as far as 50 kilometers away.

\*1 For example, if we normally see 10 unique users entering the red zone every day, and that number drops to 5 after an intervention, that's a clear signal of reduced market activity.

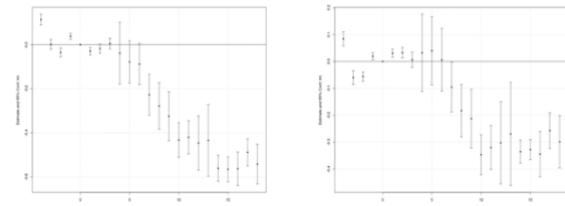


Figure: Figures depicting estimates of the dynamic effect of the Kensington Initiative on total traffic flows (left) and unique visitors (right) into the target area.

**4. Substitution, Treatment, and Long-Term Outcomes**  
Though drug demand is typically inelastic, in this case users did not turn to more dangerous substitutes. Instead, there was a measurable increase in buprenorphine prescriptions—a medication-assisted treatment for opioid use disorder—indicating a shift toward recovery rather than substitution. This supports the idea that well-executed enforcement can redirect users into treatment rather than riskier markets.

**5. Robustness and Evaluation**  
Now, about the control groups: how do we know this isn't just a fluke? used matched comparisons with similar drug markets (eg sudden external reason why there was a reduction in drug consumption) that did not undergo intervention, as well as physically similar areas without known markets. We analyzed data at both the zip code level and across neighborhood aggregates, so we could account for broader regional trends.

## THE WAR ON DRUGS How to Prevent Drug Trafficking

Efforts to prevent drug trafficking often focus on reducing drug consumption. A prominent historical example is the U.S. Prohibition era (1919–1933), during which the sale of alcohol was banned. This policy, rather than eliminating alcohol use, contributed significantly to the rise of organized crime in the United States. Over the past century, spikes in homicide rates in the U.S. have coincided with major prohibitionist efforts—first during alcohol prohibition and later during the “War on Drugs,” when the U.S. government intensified its crackdown on narcotics. This is because criminal organization fight for the control of the criminal business.



### The case of Mexico (War on drugs, 2007-)

Mexico—a large, economically challenged country sharing an extensive land border with the U.S.—has historically played a central role in the drug trade. Initially a producer of opioids, it later became a key transit hub for Colombian cocaine destined for the U.S. market. During the 1980s, the Guadalajara Cartel, led by Félix Gallardo, emerged as the first to consolidate drug production and distribution under one organization, establishing strong political connections and negotiating new drug trafficking routes through Mexico. The Guadalajara Cartel negotiated the smuggling of Colombian Cocaine through the Mexico-US border

Following the arrest of Gallardo in 1989 for his involvement in the murder of DEA agent Kiki Camarena, the cartel was fragmented into four groups. Though these cartels occasionally clashed, they coexisted under an informal arrangement with the ruling PRI party until political change in 2000 (under a fragile equilibrium).

When President Felipe Calderón of the PAN party took office in 2006, he launched a militarized offensive against the cartels, marking the beginning of Mexico's "War on Drugs." This intervention shattered the existing equilibrium, leading to intense inter-cartel violence and a surge in homicides. Between 2007 and 2015, the conflict caused more deaths than the wars in Afghanistan and Iraq over the same period.

The crackdown weakened dominant cartels, creating power vacuums and encouraging rival groups to escalate violence. The idea is that rival traffickers attempt to usurp territories after crackdowns have weakened incumbent criminals. Additionally, criminal organizations diversified into other illegal markets—such as fuel theft—due to declining profits in the drug trade. In particular, tapping into PEMEX oil pipelines became a lucrative alternative, often with inside help from corrupt employees.

#### What happened after this military operation?

##### **Trafficking Networks and the Mexican Drug War" by Melissa Dell (2015, AER)**

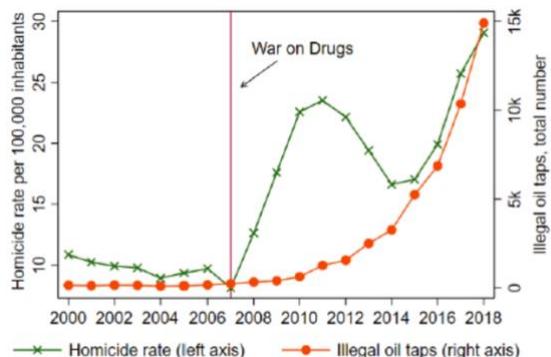
<i>Category</i>	<i>Details</i>
<b>Research Question</b>	What are the <b>causal effects</b> of drug enforcement (military crackdowns) on drug-related violence in Mexico? What are the <b>spillover effects</b> on surrounding areas?
<b>Context</b>	Post-2006 drug war in Mexico. PAN governments initiated widespread crackdowns against cartels. Violence escalated sharply (60,000+ deaths by 2012). PAN mayor can make a difference: Mayors name the municipal police chief and set policies regarding police, conduct and could assist Calderón's drug war sharing information with the PAN federal government
<b>Identification</b>	<b>Regression Discontinuity Design (RDD):</b> Compares municipalities where PAN (conservative party) barely won vs. barely lost mayoral elections. Assumes local randomization near the cutoff. Need close wins: municipalities where PAN candidates win and lose by wide margins are likely to be different. For example, support for the PAN and drug trafficking activity could be growing in tandem in a region because of economic factors, generating correlations between politics in one municipality and violence nearby. The key idea is that municipalities near the electoral cutoff (i.e., where the margin of victory is close to zero) are comparable in all respects except for the party in power.
<b>Treatment Definition</b>	Close PAN mayoral victory, interpreted as exogenous variation in enforcement intensity. PAN mayors more likely to initiate crackdowns.
<b>Data</b>	- Confidential gov't data on drug-related homicides (2007–2011) - INEGI overall homicide data - Road network - Drug seizure/confiscation data
<b>Network Model</b>	Predicts least-cost trafficking routes using a graph of Mexico's road network (Dijkstra's algorithm). Dell builds a network model of how drug traffickers move narcotics through Mexico using least-cost paths along roads. Estimated cost of trafficking along that segment, which depends on road type and topographic slope." Assumes traffickers minimize cost of moving drugs to U.S. entry.
<b>Empirical Strategy</b>	- Measure <b>direct effects</b> in treated municipalities (close PAN wins) - Use <b>predicted route shifts</b> to identify <b>spillover effects</b> on other municipalities
<b>Main Direct Result</b>	PAN victory → +27–33 drug-related homicides per 100k inhabitants per year. Over 85 percent of the total drug-related violence consists of drug traffickers killing each other.  +Police-criminal confrontations Violence persists through mayor's term.
<b>Spillover Results</b>	Crackdowns <b>divert drug routes</b> → Municipalities on rerouted paths see ↑ <b>drug seizures by 18%</b> and ↑ <b>violence by 6.2%</b> Effects larger at <b>nodes intersecting multiple routes</b>
<b>Economic Mechanism</b>	Violence increases due to <b>territorial competition</b> : increase in homicide due to rival groups attacking cartel weakened by crackdowns
<b>Robustness Checks</b>	- Balanced covariates near cutoff - No pre-trends - Alternative model specifications (including congestion in routes: If too many routes go through the same node, the cost increases) yield similar findings

<b>Placebo/Alt. Tests</b>	No similar violence increase after PAN landslide wins. Effect only for <b>close victories</b> . If they attack drug cartels where they are stronger, they just start smuggling drugs in another area.
<b>Additional Outcomes</b>	Crackdowns have <b>no significant positive labor market effects</b> . Some evidence of ↓ <b>female labor force participation</b> and ↓ <b>informal earnings</b> in spillover areas (protection rackets).
<b>Policy Implications</b>	Crackdowns without broader strategy <b>destabilize existing control</b> , worsen violence, and cause <b>diversion</b> rather than elimination of trafficking.
<b>Contribution</b>	First paper to use a <b>network equilibrium model</b> and <b>RD</b> to identify spillovers of drug policy. Supports <b>diversion hypothesis</b> in illicit market enforcement.

"Fueling Organized Crime: The Mexican War On Drugs And Oil Thefts." by Battiston, Daniele, Le Moglie, and Pinotti (2022):

War on Drugs -> narcotics less profitable -> switch to alternative (illegal) business: oil taps

<b>Category</b>	<b>Details</b>
<b>Research Question</b>	Did the 2007 Mexican War on Drugs unintentionally push drug cartels into oil thefts, and what were the socio-economic consequences? After 2007, violence surged and oil thefts rose dramatically.
<b>Motivation</b>	In addition to spatial displacement: displacement to other illegal mkts This study explores another form of displacement caused by the War on Drugs: Authors hypothesize a shift of criminal activity due to reduced drug profits and increased cartel fragmentation.
<b>Key Hypothesis</b>	Government crackdown on drugs reallocated cartel activities to oil thefts, especially by challenger cartels (e.g., Zetas), without necessarily increasing violence in affected municipalities.
<b>Identification Strategy</b>	<p>1. <b>RD Design:</b> PAN (President's party) barely winning vs. barely losing municipalities in 2007–2009 local elections (Dell, 2015 method) as quasi-random treatment.</p> <p>2. <b>DiD:</b> Pipeline vs. non-pipeline municipalities before/after 2007 to track cartel entry and socio-economic outcomes (Coscia and Rios, 2012, report the identity of all cartels present in each municipality, so we can study entry into pipeline municipalities). Diff-in-diff equation for cartel presence in:</p> <ul style="list-style-type: none"> <li>• Municipalities with/out oil pipelines</li> <li>• Before/after the war on drugs</li> </ul> <p>Incumbents: Sinaloa, Gulf, Juarez, Tijuana  Challengers: Zetas, Familia, others</p>
<b>Data</b>	<p>(a) Dominant cartels in the 1990s      (b) Dominant cartels in 2011</p> <p>Incumbents</p> <ul style="list-style-type: none"> <li>Gulf</li> <li>Sinaloa</li> <li>Juarez</li> <li>Tijuana</li> </ul> <p>Challengers</p> <ul style="list-style-type: none"> <li>Zetas</li> <li>Familia</li> <li>Beltran-Leyva</li> </ul> <ul style="list-style-type: none"> <li>- Illegal oil taps: Pemex data (2000–2014)</li> <li>- Pipeline locations: CartoCritica</li> <li>- Cartel presence: Coscia &amp; Rios (2012) using scraped news (2000–2010)</li> <li>- Elections, homicides, schooling, night lights: INEGI, NOAA</li> </ul>
<b>Main Findings</b>	<ol style="list-style-type: none"> <li>1. <b>PAN narrow-win municipalities had +6.6 illegal taps/year</b> → causal effect of War on Drugs on oil thefts.</li> <li>2. Challenger cartels (e.g., Zetas) drove the increase, not incumbents.</li> <li>3. No increase in violence in pipeline municipalities.</li> <li>4. School attendance fell for under-15 children.</li> </ol>



#### Mechanism

- Cartel "leapfrogging": new entrants diversify into oil theft where incumbents dominate drug trade. Dominant incumbents have less incentive to abandon the dominant position
- No direct violence due to non-overlapping territorial/cartel competition

#### Robustness

- Placebo RD at 2006 and with gas pipelines.
- Balanced covariates at cutoff.
- Event-study parallel trends.
- Controls for oil prices and proximity to pipelines (High oil prices → higher profits from stolen oil → could independently increase oil theft (confounder)). Controlling for this isolates the effect of the War on Drugs. Or Municipalities closer to pipelines are more exposed to potential theft opportunities. Must be held constant to ensure observed effects are not due to location advantages.)

#### Policy Implications

Crackdowns in one sector can shift crime to others; criminal innovation resembles economic behavior of legal firms.

*Pains, guns and moves: The effect of the U.S. opioid epidemic on Mexican migration\*, Daniele, la Moglie, Masera 2*

Section	Details
<b>Research Question</b>	Does a positive demand shock in an illicit market (U.S. heroin demand) affect internal and international migration from Mexico? Specifically: Did increased heroin D—caused Reformulation of Oxycontin in 2010 in the US—increase violence and migration from Mexican opium-producing areas (demand shock had considerable effects on Mexico,)?
<b>Key Hypothesis</b>	The 2010 U.S. opioid crackdown led to increased heroin demand, raising the value of poppy-suitable land in Mexico → intensified cartel competition → more violence → forced migration (domestic and to the U.S.).
<b>Data</b>	<ol style="list-style-type: none"> <li><b>Internal Migration:</b> 2010 &amp; 2015 Mexican censuses (INEGI), individual-level.</li> <li><b>U.S. Migration:</b> Matriculas consulares (2007–2016), by municipality/state.</li> <li><b>Violence:</b> Homicides, deaths (INEGI), cartel confrontations (Atuesta et al.).</li> <li><b>Poppy Suitability:</b> Constructed from soil, rain, temperature data.</li> </ol>
<b>Empirical Strategy</b>	<p>Difference-in-Differences (DID): compares high vs. low poppy-suitable municipalities before/after 2010.</p> <p>Controls for cannabis-suitability, region-year FE, municipality FE. Control: municipalities suitable for cannabis. Limit the sample to municipalities suitable for some drug (poppy or cannabis), ensuring a valid comparison group. Comparing poppy areas with non-drug areas would confound effects of cartel presence. Both poppy and cannabis areas face cartel presence.</p>
<b>Identification</b>	Assumes parallel trends in migration/violence for municipalities differing in poppy suitability, conditional on cannabis suitability and regional trends. Validated with pre-trends and placebo tests.
<b>Main Results</b>	<ul style="list-style-type: none"> <li>- Out-migration rose in poppy-suitable areas post-2010 (+0.25 p.p. for 1 SD ↑ suitability; ≈ 18% increase).</li> <li>- 94,495 extra internal migrants (2010–2015); 22,000 extra to U.S. (matriculas).</li> <li>- Most migrants went to U.S. border regions.</li> </ul>

	<ul style="list-style-type: none"> <li>- No effect on economic variables.</li> <li>- <b>Strong increase in violence: 2002 extra homicides.</b></li> </ul>
<b>Mechanism</b>	Not economic opportunity (no GDP/nightlights effects) → but increased cartel-related violence as cartels fought over valuable poppy land. Violence, not income, drove displacement.
<b>Heterogeneity</b>	Effect stronger among: <ul style="list-style-type: none"> <li>- Families with children.</li> <li>- Higher-income individuals (more likely to afford migration).</li> </ul>
<b>Literature Contribution</b>	<ul style="list-style-type: none"> <li>- First to link <i>drug production</i> area violence (not transit zones) to migration.</li> <li>- Uses direct measure of U.S. migration (matriculas) rather than proxies.</li> <li>- Extends literature on illicit markets, migration, and U.S. opioid epidemic's international consequences.</li> </ul>
<b>Policy Implications</b>	U.S. drug policy has indirect, unintended effects abroad. Heroin demand shock triggered internal displacement and cross-border migration from Mexico via violence escalation in drug production zones.

## CHAPTER 12: TAX HAVENS: TAX EVASION AND MONEY LAUNDERING

## 1 Tax Havens and Shell Companies

### I. Definitions

- **Tax Haven:** Jurisdiction offering **low taxes + high secrecy** to attract foreign assets (e.g. Panama, Bahamas, Samoa).
- **Shell Company:** **Paper entity with no real business activity**, used to hide ownership or move assets. About ownership: another shall company, a trustee, don't require registering beneficial owners, Others allow bearer shares (whoever holds the share certificate owns the company), use of nominees.

### II. Perks of Tax Havens

- A) **No taxation** for foreign investors.
- B) **Secrecy:** Allow investors to set up shell companies.
- C) **No need to carry on for economic activity** whitin the tax haven.

### III. Legal Uses of Shell Companies

1. **Asset Protection:** In war zones or unstable regimes (fear of expropriation).
2. **Legal Shield:** Insulate from poor rule-of-law systems.
3. **Strategic Secrecy:** Hide business plans (e.g., MNC CFO hides acquisitions).

### IV. Illegal Uses of Shell Companies

- A) **Tax Evasion:** Conceal foreign income .
- B) **Crime:** Reinvest Obscure proceeds (e.g., Narcotrafficker real estate in Manhattan via shell).
- C) **Corruption:** Funnel bribes via offshore intermediaries (e.g., oil firm pays Nigerian official via Cayman entity).

## 2 Empirical Evidence: *Global Shell Games*

Defintion: Corporate Service Providers (CSP) are intermediaries specialized in the incorporation of shell companies.

Design:

- 3,700 CSPs contacted. 7,400 emails from 21 fictitious clients; varied treatment (origin, corruption, secrecy premium. We want to see how they react when the alias originates from a low corruption country, or one with issues of Terrorism).

Findings:

- **Tax havens more compliant.** OECD CSPs worse at due diligence than developing countries.
- **No extra scrutiny** for corrupt-country clients.
- **Offering secrecy premiums** increased caution from CSPs.

## 3 Who Owns the Money Hidden in Tax Havens?

- **Panama Papers:** Leak from law firm *Mossack Fonseca* (active 1977–2015), among top 5 offshore service providers. Revealed **global scale:** 140 politicians from 50+ countries.

## 4 How Do Households React to a Wealth Tax Increase? (Colombia, 2010 Reform)

Context:

- Reform introduces 1% wealth tax for net wealth  $\geq 10M$  pesos.

- Below threshold: 0% tax.

**Prediction:**

- Households report less to avoid tax.
- Richest shift assets to tax havens.

**Observed:**

- Bunching below threshold.
- The marginal buncher would've reported 20% more.

**How did they do?** Take up more interpersonal debt sand reduce inventories

## 5 Did the Panama Papers Reduce Evasion?

**Theoretical Insight:** (Becker)

- Crime depends on detection probability  $\times$  penalty.
- Panama Papers increase perceived risk of detection.

**Context: Colombia, 2015–2016**

A) **2015:** Voluntary disclosure program. Pay 10% penalty of tge valye of the discplosed wealth.

B) **2016:** Panama Papers leak. Authorities learn names of offshore owners.

**Hypothesis:**

- Participation in disclosure increases, especially for those named in leak.

**Methodology:**

- **DiD Design, for every treatment group:**

- Treated: Named in Panama Papers.
- Control: Not named.
- Time: Before vs. after April 2016.

- **Result:** Disclosure likelihood  $\uparrow$  by 27.4% for treated.

## 6 Can Countries Limit Evasion by Fighting Bank Secrecy?

**Case: EU Savings Directive (Omartian, 2017)**

**Policy:**

- Effective July 2005. Targets cross-border evasion.
- Banks in the participating states have to:

1. are required to report the identify of the people that have an account in your bank individual (non-corporate) accounts held by EU residents and report account information to the account holder's home country
2. Alternatively, banks could withhold a tax on interest income for individuals residing in a EU country. The tax revenue is then transferred anonymously to the EU resident's home country.

so, example: So ex: Italian with bank account int Switzerland. Bank had to report that this Italian citizen had an account in their bank + the amount or give money to the Italian gov.

**Loophole:**

- Only individual accounts covered.
- Workaround: Shift account ownership to a shell company.

**Empirical Evidence:**

- EU banks increase offshore incorporations by 20% before July 2005.
- No increase among non-EU banks or non-EU residents.

**Fix: 2013 Amendment**

- Requires disclosure of beneficial owners behind corporate accounts.
- Unusefull to have a shell company and even a sign of evasion
- banks subject to the directive start closing the shell companies

"The Value of Offshore Secrets: Evidence from the Panama Papers", James O'Donovan, Hannes F. Wagner, Stefan Zeume (The Review of Financial Studies, 2019)

**HYPOTHESIS:**

If firms use Secret Offshore Vehicles

a) To avoid taxes

b) To finance corruption

c) To expropriate shareholders (siphoning funds to tax havens to reduce the dividends with external shareholders)

**PREDICTIONS:**

The Panama Papers leak, by exposing the offshore entities:

a) ↓ Stock Returns: as future cashflows will fall or

there will be fines for past conduct

b) ↓ Stock Returns: as future cashflows will fall or

there will be fines for past conduct

c) ↑ Stock Returns: the leak brings transparency and

reduces future illegal activity

Event study: see how firm exposure to panama papers affected their value! – 1.3% cumulative raw returns

## APPENDIX:

### 1. Lecture 10 - Money Laundering in Russia

Definition: the process of disguising the origins of illegally obtained money making it look like it came from a legitimate source.  
Why it is bad:

- allows criminal to store and make use and re-invest of the proceeds from the crimes
- fuels corruption
- more difficult for enforcers to track illegal activities
- harder for legitimate business to operate (competing with firms with illicit funds)
- boost financial instability (banks can be exposed to scandals), such funds may be inflation prices

Hermitage in the 90s was an hedge fund performing active shareholding (complaints vs corporate misbehavior). Then:

- Browder launched a high-profile campaign exposing massive asset stripping in Gazprom.
- Used shareholder rights to demand transparency and corporate governance.
- This directly threatened the interests of Kremlin-linked elites profiting from the company.

Browder was expelled from Russia. Then, the following happened (the initial investigation that revealed a 230\$ corruption fraud within the Russian government was exposed by the lawyer, Sergei Magnitsky -> arrest, torture, death. After his death Hermitage Started a joint investigation n antimony laundering): Hermitage team had liquidated all their assets in Russia, but 2 years after this happens:

Corrupt officials built a global laundering scheme. Actually, few days before the start of this story they all met in Cyprus.

1	<b>Attack on Hermitage Capital</b>	Raids on Hermitage's offices, <b>documents seized</b> .
2	<b>Ownership Transfer</b>	Such documents were later used to transfer the ownership of the company to fake owners.
2	<b>Fake Lawsuits</b>	Fake firms claimed Hermitage had agreed to sell them <b>Gazprom shares</b> . Result: claim to <b>\$376M foregone profits, \$974M court award</b> . Hermitage profits = <b>0</b> . Both the lawyers and the judge of the case and the police officer of the raid had come to cyprus.
3	<b>Tax Rebate Fraud</b>	Why 974 mln? Hermitage had paid <b>\$230M (23%)</b> in taxes. As the legal owners, the criminals could: File fake lawsuits in the company's name -> they claimed large tax refunds, pretending Hermitage had overpaid. Judge (Head of Tax Office 28, 2004–2010, in Cyprus) <b>approved same day</b> .
4	<b>Money Laundering Chain</b>	<b>Flow:</b> Russia → ex-USSR → Cyprus/Latvia/Estonia/Lithuania → EU. Note: nowadays east Europe banks will not allow Russian companies to open accounts, alternatives: crypto, Dubai, Dominica.
5		Fake directors (some was director of 110' companies), 1,609 firms at one address, <b>99 shell firms, 27 small banks</b> , fake contracts, vague payment reasons ('equipement'). Shell companies: no ordinary business, no expenses etc. Can we recognize contracts are fake even if with AI criminals can do more realistic fake contracts? Yes! These contracts are missing an underlying active business!

A. One funny case (Mrs Anna Kurepina):

- 12.2 mln € unsecured loan to an 81 yrs old Russian woman to buy a villa in Spain. Loan issued by an offshore company with a bank account in Lithuania. Unsecured with 5% interest ad no specific schedule or requirement to pay interest / principal in 10 years. No fees nor penalties for late repayment
- Invested 117\$ received as dividend 463,682\$
- Mother in law of Artyakov, oligarch



Anna Kurepina

B. They traced back some of this money went to a child friend of Putin (Panama papers)

Remark: there are some banks that conceal money laundering as their main business model (sell money laundering as a service with a given fee). Compliance department of banks should check antimony laundering. US and EU banks are harshly sanctioned (that's why they have opened compliance departments). Actually they are outsourcing from IT companies (however, IT companies, just as ranking agencies in 2008, have incentives to close deals as if they do not do it they lose the client).

Results of Hermitage efforts: prosecutions in several nations (16), some assets confiscated, emergence of the Danske Bank scandal (200 billion money laundering scandal).

**2. Workshop: some basic information on the papers I have found on the internet (I think nothing will be asked, one was not presented (the first in this synthesis), the others are not yet published (I could not find them)).**

CATEGORY	Mafia infiltrations in times of crisis: evidence from the covid-19 shock , castelluccio & rizzica (2023)
RESEARCH QUESTION	Does financial distress caused by Covid closures increase mafia infiltration into firms?
SETTING	Italy, Spring 2020 (lockdowns of non-essential businesses)
MAIN DATA SOURCES	<ul style="list-style-type: none"> <li>- CADS (balance sheets of 550K firms)</li> <li>- Direzione investigativa antimafia data (DIA)</li> <li>- Covid-sector closure list</li> <li>- Government aid take-up</li> </ul>
IDENTIFICATION STRATEGY	<p>Did, event study</p> <ul style="list-style-type: none"> <li>- Treatment = firms in sectors forced to close</li> <li>- Control = firms in sectors not closed</li> </ul> <p>First stage: Regress firm performance (e.g., revenues) on closure instrument <math>\times</math> 2020 dummy.  Exclusion restriction: Closure decision based on 6-digit ATCEO codes (granular sector), not performance-related</p> <ul style="list-style-type: none"> <li>- Use firm fixed effects and sector<math>\times</math>year and province<math>\times</math>year FE to absorb confounding trends</li> <li>- Event study shows pre-2020 trends are parallel in infiltration</li> </ul>
MECHANISM EXPLORED	Mafia acts as alternative lender when formal credit is inaccessible
MAIN EFFECTS	<ul style="list-style-type: none"> <li>- 10% revenue drop <math>\rightarrow</math> <math>\uparrow</math>4.8% mafia infiltration risk</li> <li>- Infiltration risk <math>\uparrow</math> in services and North Italy</li> </ul>
HETEROGENEITY	- Stronger in North (profitable markets)
POLICY IMPLICATIONS	Formal credit constraints increase mafia reliance; infiltration prevented by timely government grants/moratorium (loans don't work)