Replication of "Critical Recidivsm after Prison and Electronic Monitoring" by Di Tella and Schargrodsky

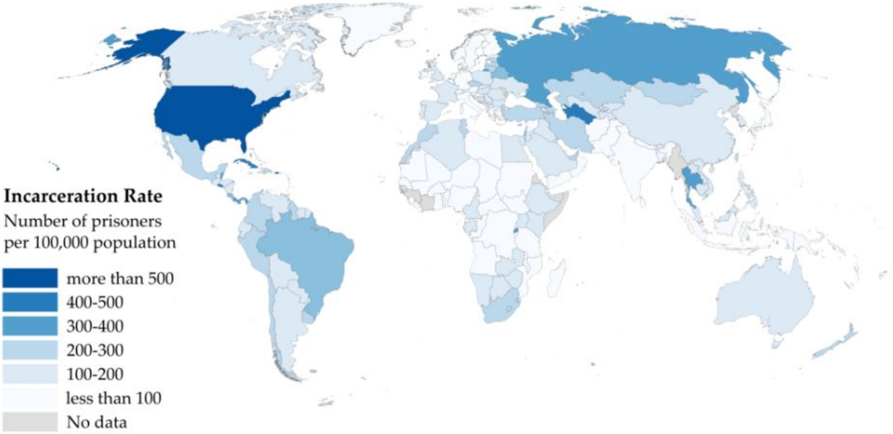
Maripjan Koshmatov Bakai Baiazbekov Aijing Sun

University of Munich

June 12, 2019

Overview

Motivation


Incarceration Rate
Number of prisoners
per 100,000 population
more than 500
400-500
300-400
200-300
100-200
less than 100
No data

Motivation

- Keeping prisons is very costly (Kuziemko 2013)
- Yet, it bears even higher cost if criminals are not isolated from society
- On the other hand, given brutality and psychologically destructive effects of prison on individuals, prisons might stimulate people to commit crimes in the future over and over again.
- So, are the other punishment tools that is more efficient compared to prison?

Motivation

- Probably the most widespread substitution for imprisonment is Electronic Monitoring (EM) of convicted individuals.

- But is it worth to implement EM? What are the risks and who should receive them instead of imprisonment?

Motivation

Rafael Di Tella

Ernesto Schargrodsky

Authors of *"Criminal Recidivism after Electronic Monitoring and Imprisonment"* (JPE, 2013)

Summary of the paper

- Aim of study: To contribute to a long-lasting debate of whether EM can be a good alternative for imprisonment
- Specifically, is EM a useful tool in reducing recidivism?
- To do that authors compare the outcomes of individuals who received EM vs that of those who were imprisoned.
- To estimate the of effect a quasi-experiment was conducted between 1998-2007 in Buenos-Aires Province of Argentine

Summary of the paper

- However, directly comparing the difference of outcomes between offenders treated with electronic monitoring vs those released from prison is naive.
- Two issues may come into play here:
  - 1.Selection Problem
  - 2.Differential risk of the target

Summary of the paper

- *Selection Problem* was resolved by random assignment of arrested individuals to judges.
- Judges were assigned to duties randomly.
- The second problem that might be a source endogeneity will be discussed below

Summary of the paper

- Authors compare effects of electronic monitoring vs imprisonment on future recidivism

$$EM_i = \pi_0 + \pi_1 Z_{1i} + \pi_2 Z_{2i} + \pi_2 X_{2i} + ... + \pi_i X_{ij} + u_i \tag{1}$$

$$Recidivism_i = \beta_0 + \beta_1 \widehat{EM_i} + \pi_2 X_{2i} + ... + \pi_i X_{ij} + u_i \tag{2}$$

Offenders released from EM

```
.          * Table 1 - Column 1
.          tab mostSeriousCrime if electronicMonitoring==1
```

Most serious crime of the alleged offender	Freq.	Percent
01 - Homicide	30	7.77
02 - Attempted homicide	8	2.07
03 - Sexual offenses	10	2.59
04 - Other serious crimes	10	2.59
05 - Aggravated robbery	224	58.03
06 - Attempted aggravated robbery	12	3.11
07 - Robbery	25	6.48
08 - Attempted robbery	22	5.70
09 - Possession of firearms	18	4.66
10 - Larceny / Attempted larceny	4	1.04
11 - Other minor crimes	23	5.96
Total	386	100.00

Offenders released from Prison

```
.        * Table 1 - Column 2
.        tab mostSeriousCrime if electronicMonitoring==0
```

Most serious crime of the alleged offender	Freq.	Percent
01 - Homicide	1,399	5.84
02 - Attempted homicide	398	1.66
03 - Sexual offenses	448	1.87
04 - Other serious crimes	482	2.01
05 - Aggravated robbery	11,647	48.58
06 - Attempted aggravated robbery	1,814	7.57
07 - Robbery	2,930	12.22
08 - Attempted robbery	1,922	8.02
09 - Possession of firearms	1,102	4.60
10 - Larceny / Attempted larceny	889	3.71
11 - Other minor crimes	945	3.94
Total	23,976	100.00

Summary of the paper

- Conclusion: There is a significant negative effect on criminal recidivism of treatment individual with electronic monitoring relative to prison.
- According to estimates, assigning convicted individual to EM on average can reduce recidivism risk by that individual between 11-16 percentage points(*ceteris paribus*).
- Here is what authors did.

Data and Replication Tools

- Datasets: Obtained from the University of Chicago website
- Tools used:
  - STATA: 14.0 and 15.1 SE
  - R

Replication steps

- Going through STATA codes to see whether specifications were entered correctly and match those that were described in the paper
- Comparison of two estimates
- Extraction of results to tables

Table: Electronic Monitoring Assignment and Type of Crimes

	Dependent variable:				
	electronicMonitoring				
	(I)	(II)	(III)	(IV)	(V)
percJudgeSentToEM	0.663***	0.660***	0.660***	0.660***	0.637***
	(0.085)	(0.085)	(0.085)	(0.085)	(0.087)
judgeAlreadyUsedEM					0.006**
					(0.002)
mostSeriousCrime02 - Attempted homicide		−0.001	−0.001	−0.001	−0.001
		(0.008)	(0.008)	(0.008)	(0.008)
mostSeriousCrime03 - Sexual offenses		0.001	0.001	0.0004	0.0003
		(0.008)	(0.008)	(0.008)	(0.008)
mostSeriousCrime05 - Aggravated robbery		−0.004	−0.003	−0.003	−0.003
		(0.004)	(0.004)	(0.004)	(0.004)
age				−0.00001**	−0.00001*
				(0.00000)	(0.00000)
numberPreviousImprisonments			−0.004***	−0.005***	−0.005***
			(0.001)	(0.001)	(0.001)
yearOfImprisonment				0.001***	0.001***
				(0.0004)	(0.0004)
Constant	0.003	0.009	0.010	−2.677***	−2.389***
	(0.005)	(0.006)	(0.006)	(0.728)	(0.722)
Observations	24,003	24,003	24,003	23,928	23,928
R^2	0.043	0.044	0.045	0.046	0.046
Adjusted R^2	0.042	0.043	0.043	0.045	0.045
Residual Std. Error	0.122 (df = 23984)	0.122 (df = 23974)	0.122 (df = 23973)	0.122 (df = 23894)	0.122 (df = 23893)
F Statistic	59.209*** (df = 18; 23984)	39.347*** (df = 28; 23974)	38.579*** (df = 29; 23973)	34.821*** (df = 33; 23894)	34.054*** (df = 34; 23893)

Note: *p<0.1; **p<0.05; ***p<0.01

Replication tables

Table: Recidivism and Electronic Monitoring OLS Regressions

	Dependent variable:				
	recidivism				
	OLS		*probit*	*OLS*	
	(I)	(II)	(III)	(IV)	(V)
electronicMonitoring	−0.092***	−0.090***	−0.405***	−0.089***	−0.086***
	(0.021)	(0.024)	(0.107)	(0.024)	(0.023)
judgeEverUsedEM					−0.017
					(0.024)
mostSeriousCrime02 - Attempted homicide		0.010		0.011	0.011
		(0.064)		(0.064)	(0.063)
mostSeriousCrime03 - Sexual offenses		−0.038		−0.045	−0.029
		(0.052)		(0.052)	(0.050)
numberPreviousImprisonments		0.167***	0.683***	0.157***	0.175***
		(0.024)	(0.089)	(0.024)	(0.024)
yearOfImprisonment		−0.058***	−0.262***	−0.057***	
		(0.018)	(0.056)	(0.018)	
Constant	0.224***	116.588***	527.711***	115.193***	1.622***
	(0.012)	(36.256)	(113.254)	(36.845)	(0.305)
Observations	1,526	1,526	1,513	1,526	1,503
R^2	0.010	0.185		0.180	0.177
Adjusted R^2	0.009	0.162		0.158	0.163
Residual Std. Error	0.399 (df = 1524)	0.367 (df = 1484)		0.368 (df = 1485)	0.368 (df = 1477)
F Statistic	15.210*** (df = 1; 1524)	8.212*** (df = 41; 1484)		8.154*** (df = 40; 1485)	12.685*** (df = 25; 1477)

Note: *p<0.1; **p<0.05; ***p<0.01

Replication tables

Table: Recidivism and Electronic Monitoring IV regressions

	Dependent Variable: recidivism				
	IV: court	IV: percJudgeSentToEM	IVs: percJudgeSentToEM, judgeAlreadyUsedEM	IV probit	IV: largeSampleEstimate
	(1)	(2)	(3)	(4)	(5)
EM1_pred	-0.112^{**}				
	(0.057)				
EM12_pred		-0.138			
		(0.093)			
EM13_pred			-0.158^{*}		-0.158^{*}
			(0.091)		(0.091)
EM14_pred				-0.174^{*}	
				(0.095)	
Constant	92.101^{***}	91.615^{***}	91.534^{***}	91.692^{***}	91.534^{***}
	(8.341)	(8.349)	(8.344)	(8.353)	(8.344)
Observations	1,503	1,503	1,503	1,494	1,503
R^2	0.168	0.167	0.167	0.167	0.167
Adjusted R^2	0.149	0.148	0.148	0.148	0.148
Residual Std. Error	0.371 (df = 1469)	0.371 (df = 1469)	0.371 (df = 1469)	0.372 (df = 1461)	0.371 (df = 1469)
F Statistic	8.985^{***} (df = 33; 1469)	8.897^{***} (df = 33; 1469)	8.924^{***} (df = 33; 1469)	9.136^{***} (df = 32; 1461)	8.924^{***} (df = 33; 1469)

Table: Recidivism and Electronic Monitoring Robustness

	Dependent Variable: recidivism			
	IVs: percJudgeSentToEM, judgeAlreadyUsedEM	IVs: percJudgeSentToEM, judgeAlreadyUsedEM	IVs: percJudgeSentToEM, judgeAlreadyUsedEM	IVs: percJudgeSentToEM, judgeAlreadyUsedEM
	(1)	(2)	(3)	(4)
EM161_pred	−0.243**			
	(0.105)			
EM162_pred		−0.151		
		(0.117)		
EM163_pred			−0.154*	
			(0.091)	
EM165_pred				−0.210**
				(0.094)
incomeProfession	0.00005*			
	(0.00002)			
spouse		0.029		
		(0.025)		
familyVisits		0.048		
		(0.068)		
Constant	80.358***	91.259***	94.417***	89.300***
	(10.415)	(9.856)	(8.454)	(8.442)
Observations	941	1,147	1,503	1,441
R^2	0.162	0.169	0.170	0.169
Adjusted R^2	0.131	0.143	0.150	0.150
Residual Std. Error	0.372 (df = 906)	0.383 (df = 1111)	0.371 (df = 1467)	0.368 (df = 1407)
F Statistic	5.156*** (df = 34; 906)	6.471*** (df = 35; 1111)	8.574*** (df = 35; 1467)	8.685*** (df = 33; 1407)

Replication tables

Table: Recidivism and Escape within EM

	Dependent variable:		
	recidivism		escapees
	(I)	(II)	(III)
	(1)	(2)	(3)
EMLengthTotalPrisonRatio	−0.087		
	(0.056)		
mostSeriousCrime02 - Attempted homicide	0.079	0.073	−0.088
	(0.118)	(0.124)	(0.079)
mostSeriousCrime03 - Sexual offenses	0.135	0.122	0.209
	(0.129)	(0.127)	(0.163)
numberPreviousImprisonments	0.119**	0.132***	0.135***
	(0.047)	(0.046)	(0.048)
yearOfImprisonment	−0.033***	−0.032***	−0.003
	(0.008)	(0.008)	(0.010)
Constant	65.583***	65.105***	6.985
	(16.191)	(16.205)	(20.380)

An obstacle during Replication Process

- Note: While reproducing the code, everything ran smoothly, except for Column 4 of Table 5, where 15.1 SE version of STATA did not allow clustering for IV probit estimation.

- However, no such problem occurred in STATA 14.0 or R.

- Moreover, every regression estimates in all other tables and columns was clustered according to the same variable, but no such problem occurred.

Measurement Analysis

- Re-estimation was done via redefining Age and Total detention period variables in years instead of days.

- When focusing on the sub sample of judges who had at least 20 cases instead of at least 10 cases that were originally specified by authors, effect of EM is still statistically significant. However, once we restrict sample to judges who at least had 30 cases, the estimation results become insignificant at 5% significance level.

Measurement Analysis

- In the original work escape from EM was not considered as a recidivism. But once it starts to be counted as a crime, IV estimates fail to give significant results at 5% level
- Also, once sample is restricted to criminals aged between 18-30, IV results also fail to be significant at 5% significance level.

Theory of change I

To contribute further to the topic of effectiveness of EM, the following could be considered in the future as a tool for policy evaluation:

- Diff-in-Diff estimation
- Regression Discontinuity

Theory of Change I (Diff-in-Diff estimation)

- Select a city(province/country) where EM was implemented
- Obtain data about crime category and recidivism before and after EM was introduced.
- Obtain the same data on one or more cities (provinces/countries) with similar characteristics where EM was not implemented(preferably in a consecutive 10 years)
- Make sure that Parallel trend assumption holds
- Implement DiD method to the see the effect of EM on future recidivism.

Theory of Change I (Regression Discontinuity)

- Motivation: Criminal Law of every country determines a severity of punishment based on how large was the actual or potential damage to a society.
- However,since the word "huge" is highly subjective, the same Criminal Law measures it quantitative term(i.e. there is a threshold). for example, consider the case with selling drug distribution, fraud, etc.
- In other words, threshold determines the severity of punishment
- In this case it might be useful to compare the effects of EM assignment to imprisonment.

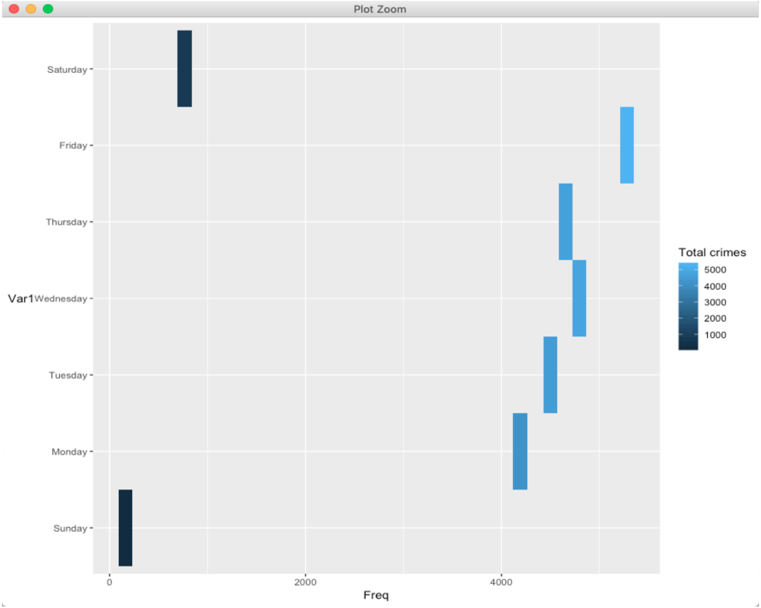
Theory of Change

- Objectives: Effects of EM on educational outcomes
- Methods : IV to assess the causal effects of EM on young offenders educational outcome. Experiment exploiting a reform in Denmark in 2006 introducing EM to all offenders under age of 25 with max. prison sentence of 3 months.
- Results : The EM increases the completion rates of upper secondary education by 18 % points among program participants 3 years post-release.
- Two studies exploit reform - *negative effect on recidivism* (Jorgensen 2011) and *positive effects on subsequent labor market outcomes* (Andersen and Andersen 2014)

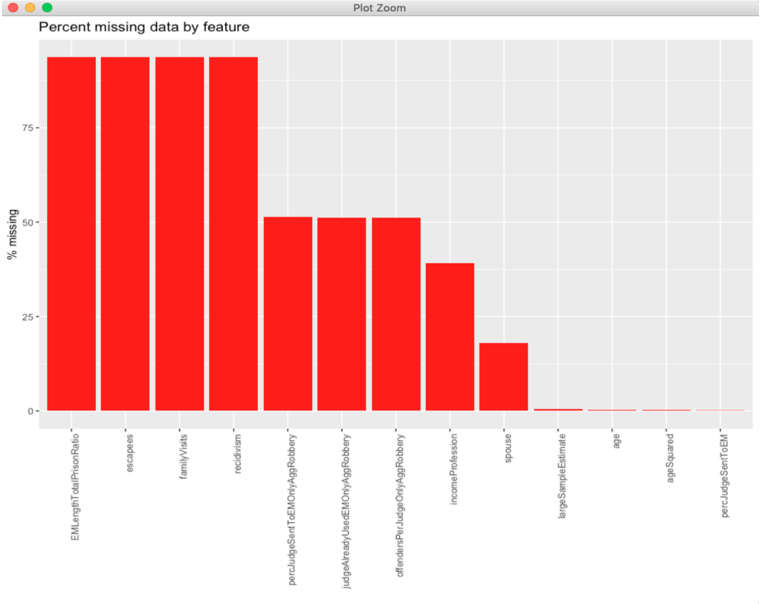
Theory of Change (Further Extension)

- Application of Decision Trees to obtain the probability of recidivism for each individual in the data set for the given characteristics
- Tools : Classification and Regression Trees (CART) model
  - Random Forest

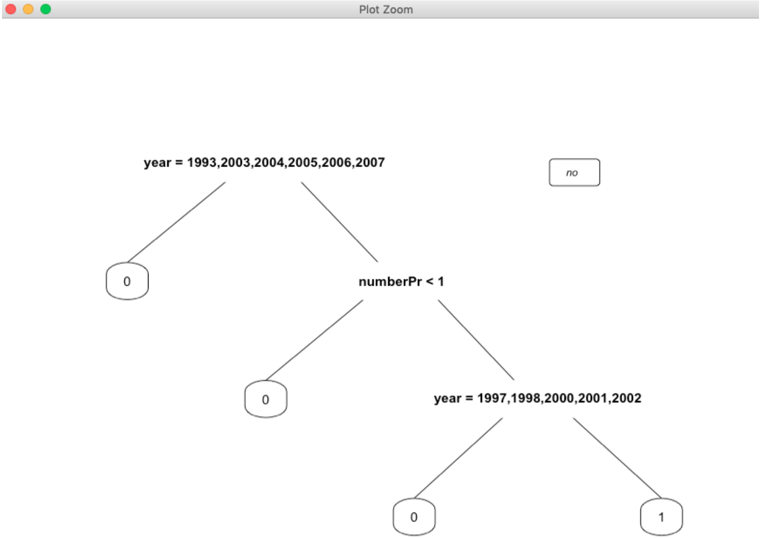
Total Crime


Plot Zoom
Saturday
Friday
Thursday
Var1
Wednesday
Tuesday
Monday
Sunday
0
2000
4000
Freq
Total crimes
5000
4000
3000
2000
1000

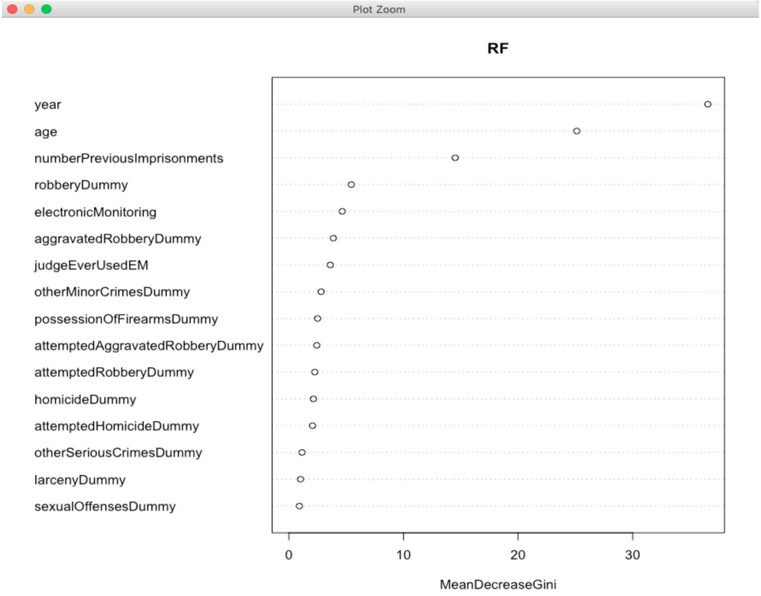
Total Missing Values in %



Decision Tree



Variable Importance Plot



References

Di Tella, Schargrodsky (2013)
Criminal recidivism after Electronic Monitoring and Imprisonment
Journal of Political Economy

Becker (1968)
Crime and Punishment
Journal of Political Economy

Larsen, Britt (2017)
Educational Outcomes After Serving with Electronic Monitoring
Journal of Quantitative Criminology

Thank you for your attention

GitHub