The Impact of Payday Lending on Crimes

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Introduction

Police departments located in states allowing payday lending report 14.34% more property crimes than the police departments located in states not allowing payday lending. I also find that the police departments located in counties bordering with states allowing payday lending report more property crimes. Those results are driven by the financial pressure induced by payday loans. Furthermore, the impact of payday lending concentrates in areas with a higher proportion of the minority population.

What I did?

- I study the effect of payday lending on crimes
- I find that payday lending affecting crimes because of the financial pressure

Hypothesis

Financial stain theory (Kubrin et al., 2011):
Financial distressed borrowers become the offenders

McIntyre and Lacombe (2012)-Personal indebtedness
Garmaise and Moskowitz (2006)-High interest rate motives crimes

Identification

State level Probit regression:

$$Prob(Allowed_{it}) = \alpha_t + \beta_1 X_{it} + \varepsilon_{it} \; (1)$$

Difference in Differences (DID) Model

$$\begin{aligned} &Property\ crime_{it} \\ &= \alpha_{s(i)} + \alpha_t + \beta_1 Treat_i \times Post_t + \beta_2 Treat_i \\ &+ \beta_3 Post_t + \gamma X_{st} + \delta Z_{ct} + \varepsilon_{it} \; (2) \end{aligned}$$

Data

State laws:

(1) Statutes,

(2) Superseded statutes

(3) Session laws

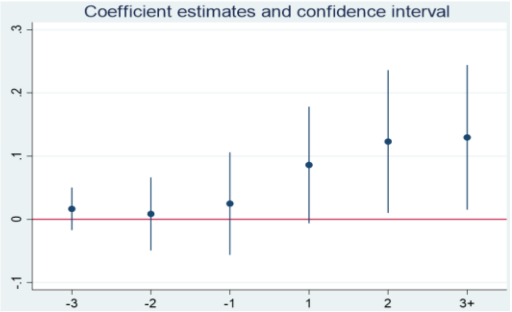
- Uniform Crime Reporting (UCR) program
- 1985 to 2014
- Dependent variable-Natural logarithm of property crimes

Results

	Ln(Property crime)	Ln(Property crime)	Ln(Burglary)	Ln(Burglary)	Ln(Larceny)	Ln(Larceny)	Ln(Motor theft)	Ln(Motor theft)
Panel A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat×Post	0.100**	0.134***	0.112**	0.130**	0.104**	0.139***	0.096	0.133**
	(0.045)	(0.043)	(0.050)	(0.053)	(0.042)	(0.039)	(0.066)	(0.056)

Dynamic Analysis

$$Property\ crime_{it} = \alpha_s + \alpha_t + \alpha_j + \sum_{k=-3}^{k=3} \beta_k Treat \times Year_k + \gamma X_{st} + \delta Z_{ct} + \varepsilon_{it} \; (3)$$



Channel-Placebo Test

	Ln(Violent crime)	Ln(Violent crime)	Ln(Murder)	Ln(Murder)	Ln(Rape)	Ln(Rape)	Ln(Robbery)	Ln(Robbery)	Ln(Assault)	Ln(Assault)
Panel A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat×Post	0.057	0.039	-0.035	-0.036	0.065*	0.047	0.000	0.040	0.050	0.019
	(0.044)	(0.042)	(0.028)	(0.024)	(0.036)	(0.033)	(0.059)	(0.047)	(0.044)	(0.042)

State×Year fixed Effects

$$Proeprty\ crime_{it} = \alpha_{s \times t} + \beta_1 Access\_X\_Y_{ct} + \gamma Z_{ct} + \varepsilon_{it} \; (4)$$

	Ln(Property crime)	Ln(Property crime)	Ln(Burglary crime)	Ln(Burglary crime)	Ln(Larceny crime)	Ln(Larceny crime)	Ln(Motor theft crime)	Ln(Motor theft crime)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Access_0_30	0.174**	0.169*	0.062	0.060	0.049	0.075**	0.027	0.040
	(0.084)	(0.097)	(0.047)	(0.052)	(0.067)	(0.033)	(0.104)	(0.076)
Access_30_40	0.062	0.076	0.073	0.083	-0.059	0.023	-0.059	0.027
	(0.144)	(0.140)	(0.120)	(0.117)	(0.130)	(0.089)	(0.158)	(0.107)

Cross-Sectional Test

Panel A.	Ln(Property crime)	Ln(Property crime)	Diff in (1)
African American	High	Low	
	(1)	(2)	(3)
Treat×Post	0.146***	0.097*	0.049*
	(0.048)	(0.051)	P=0.086