Présentation article : Do digital technologies reduce racially biased reporting ? Evidence from NYPD administrative data

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Plan

Introduction

- J.Watson, G.Burtch, B.N.Greenwood ; Princeton University, April 2024
- Subject : Reporting bias in police investigations
- Does technology help reducing this reporting bias ?

Method

1. Data : Weekly and by precinct “Stops” data of NYC
2. 72 weeks to rollout the Iphones in the 77 precincts
3. Staggered Difference in Difference : Based on the staggered rollout of Iphones in police investigations week by week in 2017 and 2018. First week of Iphone implementation : week 48. Last week of implementation : week 72.
4. Coded on R
5. dependant variables : different type of stops
6. White vs Non-White
7. Crime vs No Crime

Staggered Diff-and-Diff with ETWFE

An Empirical Two-Way Fixed Effects (ETWFE) approach is used in the article.

- Extends traditional DiD analysis to handle data with variations across both units (precincts) and time (weeks).
- Relevant for staggered treatment adoption times and varying intensities across units.
- The etwfe function from the etwfe package is used in the code.

Models are estimated for different outcomes like total stops, stops involving nonwhite individuals, null stops, etc.. all using a Poisson distribution assumption which is appropriate for count data.

Results

First result of the effect of Introduction of Iphones on different types of stops :

	All stops	Unproductive stops	Stops leading to arrest	Stops involving use of force	Complaints
Post-iPhone	0.480** (0.229)	0.459*** (0.154)	0.035 (0.070)	0.087 (0.073)	−0.035 (0.055)
Observations	5,467	5,467	5,390	5,390	5,467

This table shows estimates for the ATT of smartphone introduction in the NYPD on stops, nonproductive stops, arrests, use of force, and complaints. All columns estimate the ATT using the pooled QMLE of Wooldridge (20). SE are clustered at the precinct and week-year level. *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$.

- Introduction of Iphone :
  - Increases the number of stops by 0.48 (18% increase compared to pre-treatment)
  - Increases the number of unproductive stops (stops which did not lead to arrests) by 0.46 26% over the baseline.

Results

Effect of Introduction of Iphones on stops by ethnicity :

	White stops	Non-White stops	Unproductive stops (non-White)	Stops leading to arrests (non-White)	Stops involving use of force (non-White)
Post-iPhone	−0.055* (0.033)	0.537*** (0.195)	0.469*** (0.128)	0.070 (0.062)	−0.006 (0.029)
Observations	5,467	5,467	5,467	5,390	5,390

- Introduction of Iphones:
  - Decreases in reports of stops involving White (-0.055)
  - Increase of stops involving Non-white stops by 22% over the average stop per week
  - The other results are non significant

Results

Effect of Iphone introduction according to precinct crime rate
Below average vs above average :

Table 3. Effect of iPhone introduction by NYPD precinct crime rate

	All stops
Post-iPhone (precinct below avg. felony rate)	−0.224 (0.323)
Post-iPhone (precinct above avg. felony rate)	0.776* (0.430)
Observations	5,467

- Iphone introduction
  - Decreases stops in low crime precinct
  - Increases stop in high crime precinct
- Interpretation : Under-reporting of stops in high crime precincts before Iphone introduction

Results

Effect of Iphone introduction according to population densitiy :

Table 4. Effect of iPhone introduction by NYPD precinct demographics

	All stops
Post-iPhone (precinct below NYC avg. White population)	0.967* (0.585)
Post-iPhone (precinct above NYC avg. White population)	0.098 (0.216)
Observations	5,467

- Iphone introduction:
  - leads to a higher number of stops in precincts whith a larger proportion of non-white citizens
  - reveals that under-reporting was concentrated in areas characterized by a greater proportion of non-white citizens

Staggered Diff-and-Diff in another way

The authors use the Estimated Two way Fixed Effect (ETWFE)

We decided to use an alternative way to implement a staggered diff-and-diff :

- Utilizes a classical Difference-in-Differences (DiD) model combined with robust standard errors and clustering by precinct and week.
- We Use the generalized linear model (glm) with a Poisson distribution to estimate Diff-and-diff models for the specified variables (stops, unproductive stops, arrests, use of force, complaints etc).

  The classical DiD approach as implemented here is straightforward, focusing on before-and-after comparisons within treated units.

Table 1 : Average effect of Iphone on stops and complaints

	All stops	Unproductive stops	Stops leading to arrest	Stops involving use of force	Complaints
Post-iPhone	0.480** (0.229)	0.459*** (0.154)	0.035 (0.070)	0.087 (0.073)	−0.035 (0.055)
Observations	5,467	5,467	5,390	5,390	5,467

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(a) Article results

Outcome Variable	Coefficient (Post)	P-Value	Significance
Stops	0.1123	0.002983512	***
Unproductive Stops	0.1340	0.003617240	***
Stops leading to arrests	0.0753	0.163701488	
Stops involving use of force	0.1095	0.270088193	
Complaints	0.0131	0.745081923	

(b) Results with RDD

Staggered Diff-and-Diff

Table 2: Average effect of Iphone by stop ethnicity

	White stops	Non-White stops	Unproductive stops (non-White)	Stops leading to arrests (non-White)	Stops involving use of force (non-White)
Post-iPhone	−0.055* (0.033)	0.537*** (0.195)	0.469*** (0.128)	0.070 (0.062)	−0.006 (0.029)
Observations	5,467	5,467	5,467	5,390	5,390

(c) Article results

Outcome Variable	Coefficient (Post)	P-Value	Significance
Non-White Stops	0.1267	0.001476125	***
White Stops	0.1166	0.210721707	
Non-White unproductive Stops	0.1426	0.003005938	***
Non-White Arrests	0.0952	0.094575180	*
Non-White stops involving use of Force	-0.0343	0.659433124	

(d) Results with RDD

Regression discontinuity design

Method :

$$Y_{it} = \beta_0 + \beta_1 \cdot \text{Treated}_{it} + \beta_2 \cdot \text{Distance}_{it} + \beta_3 \cdot (\text{Treated}_{it} \times \text{Distance}_{it}) + \epsilon_{it}$$

- Y_{it} : Number of stops in the precinct i à la semaine t.
- Treated_{it} : Dummy Variable : 1 if t is after Iphone introduction (year_week $\geq$ g_iphone), 0 otherwise.
- Distance_{it} : Distance to the threshold (year_week $-$ g_iphone).
- β_0 : Intercept.
- β_1 : Coefficient of the average effect on treatment (post-iPhone).
- β_2 : Coefficient of the distance to the threshold.
- β_3 : Coefficient of interaction between of treatment effect to distance.
- ϵ_{it} : Error term

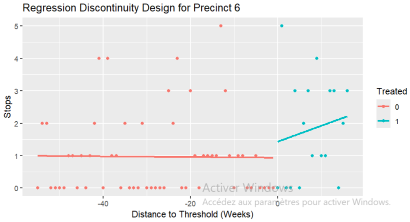
Regression discontinuity design

Interest of the RDD method :

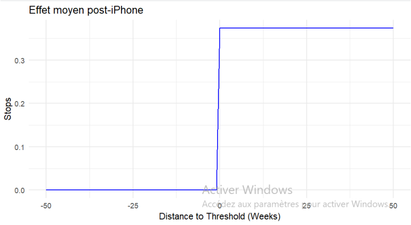
- Local Identification of Causal Effects: RDD allows for the identification of the local average treatment effect(LATE)
- Less influenced with Time Effects: RDD is less affected by time effects because the comparison is between units close to the threshold
- Continuity assumption : The key assumpion in RDD is that units above and below the threshold are comparable

Results

Graphical results : A sharp design



(e) Example : rdd for precinct 6



(f) result of treated : sharp design

Table 1

- Table 1

	All stops	Unproductive stops	Stops leading to arrest	Stops involving use of force	Complaints
Post-iPhone	0.480** (0.229)	0.459*** (0.154)	0.035 (0.070)	0.087 (0.073)	−0.035 (0.055)
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(g) Article results

Average effect of Iphone on stops and complaints

All stops	Unproductive stops	Stops leading to arrests	Stops involving use of force	Complaints
0.521	0.451	0.113	0.367	-0.088

(h) Results with RDD

- We aggregated all the LATE in order to get an approximation of the ATE

Table 2

- Table 2

	White stops	Non-White stops	Unproductive stops (non-White)	Stops leading to arrests (non-White)	Stops involving use of force (non-White)
Post-iPhone	−0.055* (0.033)	0.537*** (0.195)	0.469*** (0.128)	0.070 (0.062)	−0.006 (0.029)
Observations	5,467	5,467	5,467	5,390	5,390

(i) Article results

Average effect of Iphone by stop ethnicity

White stops	Non-White Stops	Unproductive stops(non-White)	Stops leading to arrests(non-White)	Stops involving use of force(non-white)
0.105	0.413	0.322	0.121	-0.035

(j) Results with RDD

Possible Limitations

- Can we say that Police patrol only stay in his precinct ? If not we definitely have a kind of externalities in the other precincts which have not yet been treated.

- Possible bias due to low orders of magnitude

- It is possible that changes in enforcement priorities, or significant political events could have influenced the reporting behavior of officers independently of the technology.

To Go Further

- Look at how technology spreads between neighbourhoods with geographical coordinates.
- More precise ethnic data than a White-Non-White binary analysis, and more precise crime-type data.
- Longitudinal Analysis : Assess whether the initial increase in reporting is sustained over time or if officers develop new ways to circumvent reporting
- Examine other forms of bias in police reporting, such as biases related to gender, socioeconomic status