Measuring State Attorney Kim Foxx's Impact on Sentencing Outcomes in Cook County: A Regression Discontinuity in Time Approach

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PPOL564: Final Class Status Update
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Outline

- Motivation
- Research Questions
- Data
- Methods
- Results thus far
- Limitations/Next Steps

Motivation

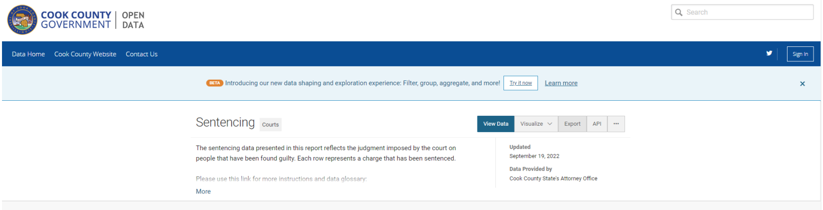
- Marshall Project: State's Attorney Foxx has dismissed "thousands" more cases than predecessor.
- Are there racial disparities among dismissed cases?

Research Questions

- Our main goal was to analyze the impact State Attorney Foxx's entry had on both race and gender. We did this by looking at these questions:
  - Does State Attorney Foxx's entry into office have any impact on racial disparities in terms of likelihood of incarceration?
  - Does State Attorney Foxx's entry into office have any impact on racial disparities in terms of sentencing length?
  - How does State Attorney Foxx's entry effect several key characteristics that include, but are not limited to, crime types and defendant's gender?
  - Does State Attorney Foxx's entry into office have any impact on racial disparities in terms of sentence type?
  - Does State Attorney Foxx's entry into office have any impact on gender disparities in terms of sentence type?

Data acquisition: sources

- We acquire the `intake` and `sentencing` datasets by downloading them from Cook County Government's website.
- The datasets are available for exports in csv formats



Data cleaning

For both datasets, the cleaning procedures can be grouped into into four tasks:

1. Cleaning basic demographics
2. Cleaning date-time variables
3. Cleaning outcome variables
4. Filtering to create analytic datasets

Data cleaning - Demographics

- We start by looking at the `value_counts` or distribution of key columns: `RACE`, `GENDER`, `AGE_AT_INCIDENT`, among others to look at anomalies in data entries
- For race, we recode:
  - `Black` or `White/Black [Hispanic or Latino]` as Black
  - `White` or `CAUCASIAN` as white
  - We code Albino, Biracial, and Unknown race groups as `nan`
- For age, we winsorized the data to its 99.995$^{\text{th}}$ percentile
- Other columns are relatively straightforward

Data cleaning - Date-time

- Using `regex`, we cleaned up entries where the year's second digit are switched with the third digit (e.g. 2109 instead of 2019)
- Key date variables in each datasets:
  - `intake` = `FELONY_REVIEW_DATE`
  - `sentencing` = `SENTENCE_DATE`
- We convert each of the cleaned date fields to `Pandas` date-time objects, and extracted their year, month and day components
- We then generated `timedelta` objects denoting time differences (in months, weeks and days) relative to State Attorney Foxx's entry into office – 1 December 2016.
- The timedelta object will be used as running variable in our RDiT approach

Data cleaning - Outcome variables

- In the `intake` data, our outcome of interest is `felony_is_rejected` – this tells us whether the defendant's felony review resulted in rejection / disregard
  - Recoding is relatively straightforward
- In the `sentencing` data, the outcome variable is:
  - Whether incarcerated (incarcerated if `COMMITMENT_TYPE == Ïllinois Department of Corrections"`)
  - Whether on probation (probation if `COMMITMENT_TYPE` contains word "Probation")
  - Sentencing length – for this, we converted the different `COMMITMENT_UNIT` to days, and removed non-sensical units e.g. `['Term', 'Dollars', 'Pounds', 'Ounces', 'Kilos']`

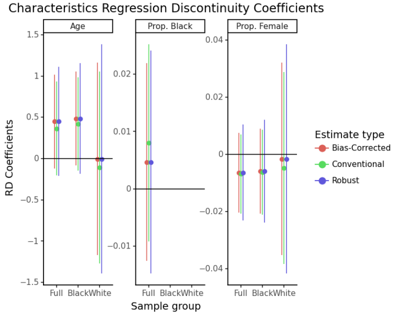
Data cleaning - Filtering

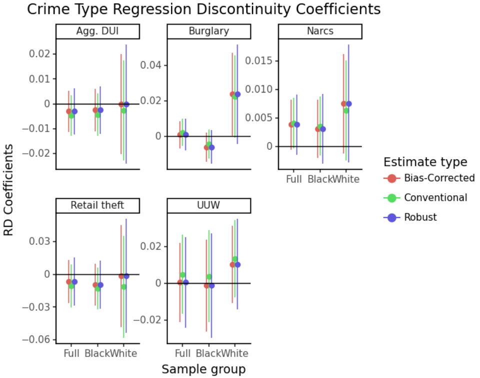
- For `intake` dataset, we filter against years that are higher than 2022
- For `sentencing` dataset, we filter:
  - Against years that are above 2022
  - Against 0 `COMMITMENT_TERM` and non-null `COMMITMENT_UNIT` (e.g. 0 years, 0 months, etc.)
  - Filter to cases where only one participant is charged, to avoid complications on plea bargains or informing from other participants that also affect the focal participants

Methods: Regression analysis

- Our analysis implements a sharp regression discontinuity (RD) approach:
  - Sharp discontinuity on State Attorney Foxx's entry
  - Time as the running variable
- We heavily rely on the approach proposed by Calonico et al. [2014] on robust data-driven inference in discontinuity designs
- Identification: defendants across either side of the cutoff (before and after Attorney Foxx's entry) are sufficiently similar such that their only difference is Attorney Foxx's entry into office

Similar characteristics on either sides of cutoff





Methods: Regression analysis

Setup:

$$Y_t = \begin{cases} Y_t(0) & \text{if } T_t < \bar{t} \\ Y_t(1) & \text{if } T_t \geq \bar{t} \end{cases}$$

$\tau = \mu_+ - \mu_-,$ with $\mu_- = \lim_{t \to \bar{t}} \mu(t),$ and $\mu_+ = \lim_{\bar{t} \to t} \mu(t)$

$$\mu(t) = \mathbb{E}(Y_t | T_t = t)$$

where:

- t denotes time period t
- $\bar{t}$ is the time cutoff
- τ is the treatment effect

Methods: Regression analysis

More specifically, we're estimating a local polynomial RD estimator that is described as follows:

$$\hat{\tau}_p(h_n) = \hat{\mu}_{+,p}(h_n) - \hat{\mu}_{-,p}(h_n)$$

Where each of the term represents the intercepts for local polynomial (of p-th order) of the selected control and treatment units, respectively.

We implement estimations using Python's `rdrobust` package, using MSE-optimized bandwidth selector (the default bandwidth selector in `rdrobust` package)

Descriptive statistics - Demographics

Characteristics	**Levels**	**Intake Data**		**Sentencing**	
		N	%	N	%
Sex	Male	317431	85.93%	130070	86.57%
	Female	51968	14.07%	20175	13.43%
Race	Black	303727	82.22%	122898	82.5%
	White	65672	17.78%	27347	17.5%

Dataset	**Summary Statistics of Age**						
	N	**Mean**	**Min**	**P25**	**P50**	**P75**	**Max**
Intake	361098	34.18	17	24	31	44	81
Sentencing	148328	33.08	17	23	30	42	81

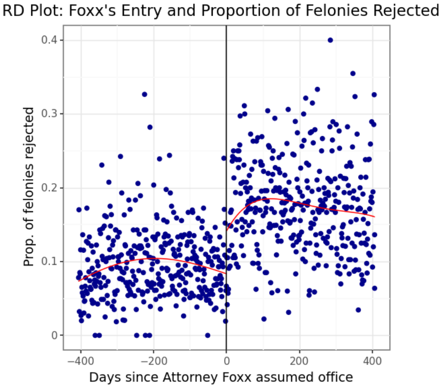
Descriptive statistics - Outcome variables

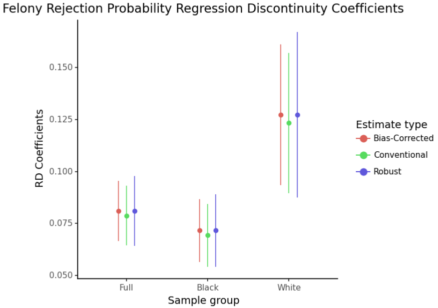
Race	Outcome variables				
	Prop. Rejected Felonies	Prop. Incarcerated	Prop. on Probation	Sen. Term	
				Mean	SD
All	0.066	0.538	0.388	3.058	4.64
Black	0.066	0.572	0.359	3.156	4.87
White	0.069	0.388	0.517	2.616	3.395

Results: Preview

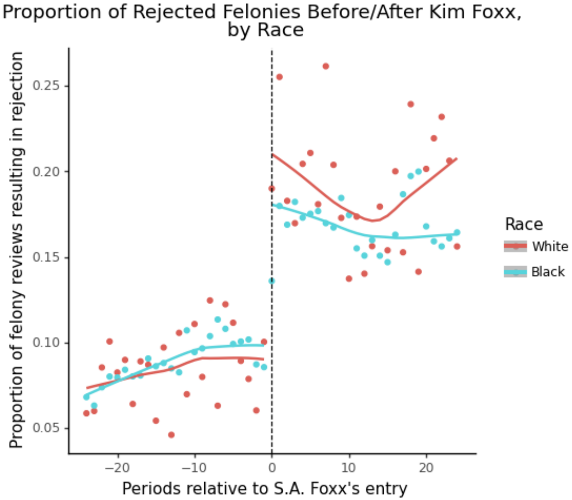
- State Attorney Foxx exerted impacts across different sentencing stages
- We observe stronger impact in the **upstream, intake stage**, but somewhat weaker effect on the **downstream sentencing stage**
    - S.A. Foxx's entry led to 8.1 pp increase in probability of felony rejections, and this effect is mostly driven by retail theft crimes (32 pp increase) – consistent with her new policy on the prosecution of retail theft crimes
    - Incarceration rate also dropped by 6.8 pp following her entry into office.
    - No significant effect on likelihood of probation or sentencing length
- Black-white gaps in sentencing outcomes largely remain unchanged following Attorney Foxx's entry
    - The effects (or lack thereof) on incarceration, probation and sentence length are relatively equal across Black and white defendants
    - However, Black female defendants experienced larger reductions in sentence length
    - Probability of felony rejection increased disproportionately among whites (by 12.7 pp) compared to Black defendants (7.2 pp), likely widening the Black-white gap

Attorney Foxx's entry led to increases in felony rejection rate, especially among white defendants...

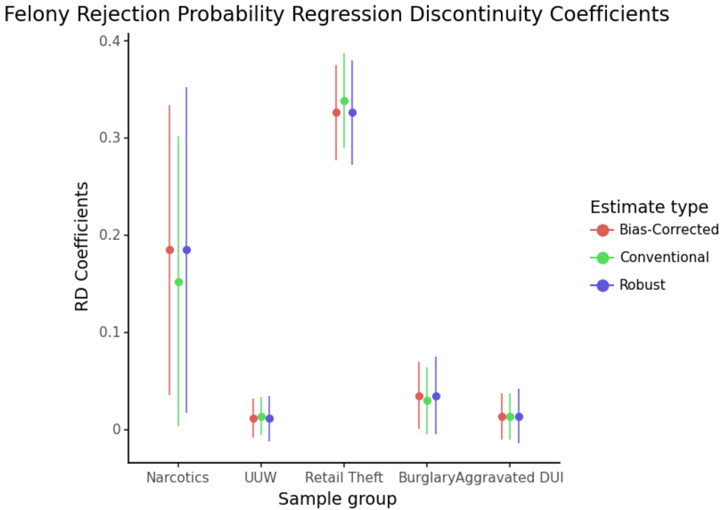




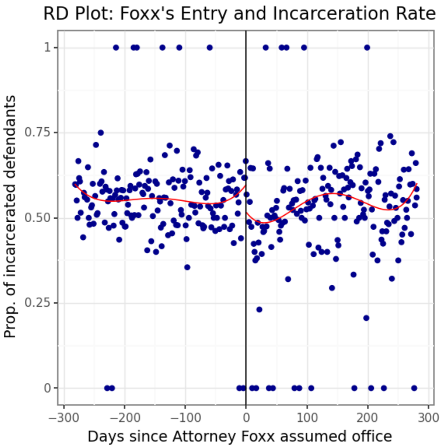
... and they are likely to widen the Black-white gap in felony rejection rates

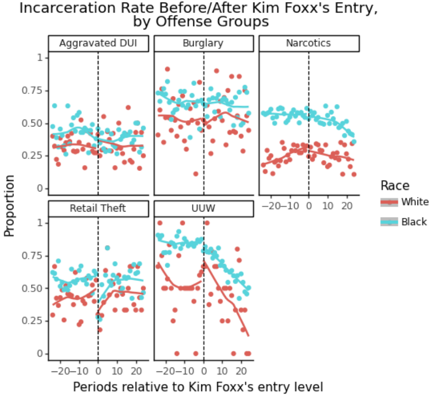


Felony rejection increases are concentrated among retail theft offenses

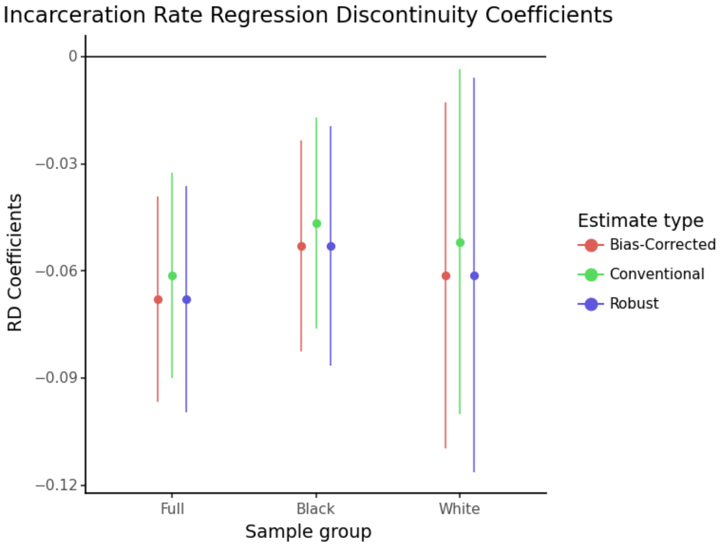


Decreases in incarceration rates are also observed, largely driven by reductions in retail theft incarcerations

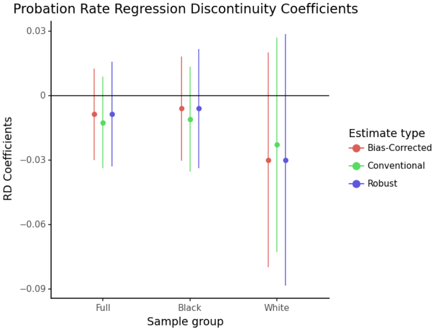


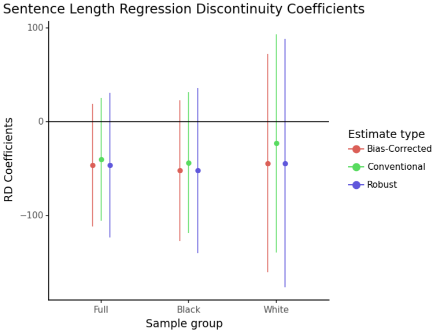


Incarceration rate effects are relatively equal across Black and white defendants

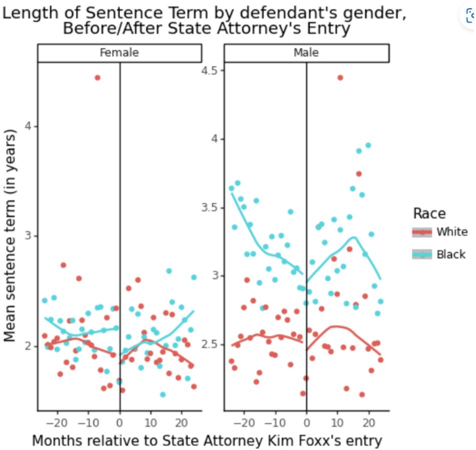


No strong effects on probation rate or sentence lengths...





...Although Black females experienced stronger reductions in sentence length.



Stronger term reductions are also observed
for **narcs** and **retail theft** offenses.

Next steps

- Complicate model of felony life cycle
- More robustness checks to address potential methodological pitfalls
- Suggestions from Hausman and Rapson (2018):
    - Placebo tests
    - "Donut" estimation
    - Autoregression tests

S. Calonico, M. D. Cattaneo, and R. Titiunik. Robust data-driven inference in the regression-discontinuity design. *The Stata Journal*, 14 (4):909–946, 2014.