

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

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There is growing discourse around the movement to elect progressive prosecutors to office like State Attorney Kim Foxx in Illinois. Progressive prosecutors are touted for their commitment to reducing mass incarceration and racial disparities in the criminal justice system. Previous work has shown that State Attorney Foxx has reduced the number of cases pursued in Cook County, Illinois; however, there is little research on the disparate impact by race of this case reduction. We use data provided by the Cook County government to analyze the impact of State Attorney Foxx assuming office by race and gender. In line with previous work, we find that the decrease in prosecutions was mainly driven by Foxx’s reduction of prosecuting retail theft cases. Additionally, we find that the proportion of cases rejected is higher for white defendants than Black defendants, a margin that has grown since Foxx assumed office. State Attorney Foxx also had an impact on incarceration, with limited impact on the racial disparities of the incarceration gap. We also find that her tenure had limited impact on the likelihood of probation and length of sentence terms. These results bring to question whether Foxx is fulfilling her mandate as a progressive prosecutor.

Criminal Justice | Carceral System | Progressive Prosecutor | Racial Gaps in Sentencing Outcome | Regression Discontinuity | Cook County

Prosecutors play a vital role in the American carceral system. They are the main officials who decide whether to pursue charges in a case, or to drop it. In the wake of the nascent social movement of the 2010s that came to be known as Black Lives Matter, as all aspects of the carceral system from police to prisons were called into question, attention came to the prosecutor’s office as a site for making important reforms. One might imagine that the growing social consciousness brought by the Black Lives Matter movement was one factor that contributed to the wave of progressive prosecutors elected across the country in the 2010s, like Larry Krasner in Philadelphia, George Gascón in Los Angeles, and Kim Foxx in Cook County, Illinois. If a mandate of ending racial disparities assisted in these prosecutors’ elections to office, one measure of their fulfillment of this mandate is the effect of their incumbency on racial disparities in outcomes. We use a regression discontinuity in time method to examine the effect of Kim Foxx’s tenure as the Cook County State’s Attorney on racial disparities in sentencing outcomes.

Related Work

Progressive prosecutors seek to reduce mass incarceration and the racial disparities that accompany it. Davis (2019) describes the push towards progressive prosecutors like Kim Foxx. Davis details how Foxx’s predecessor Anita Alvarez was "tough on crime" and heavily prosecuted most crimes. This combined with accusations of misconduct likely contributed to Alvarez’s defeat. Once Foxx took office, she announced that they would not charge individuals with retail theft unless the amount stolen exceeded \$1,000 (previously \$300) or the individual has over ten felonies.(1) Daniels (2019) finds that through 2019, Foxx had

Significance Statement

The movement to elect progressive prosecutors like Attorney Foxx is on the rise in the United States. Progressive prosecutors promise to decrease mass incarceration and the racial incarceration gap; however, State Attorney Foxx has seemingly only kept one of those promises. Further, while previous work has shown that State Attorney Foxx’s tenure has reduced the number of cases pursued in Cook County, Illinois, there has been limited research on the disparate impact by race of this case reduction. Our research fills in that knowledge gap by looking at the impact of her tenure on sentencing outcomes across Black and white defendants, thus enabling us to look at whether racial outcome gaps have changed since Attorney Foxx assumed office.

Author One, Author Two, and Author Four are involved in the data cleaning process. Author Three is heavily involved in the paper write-up and the paper’s editorial decisions. All authors are significantly involved in the paper’s analysis process.

We hereby declare that we have no significant competing financial, professional or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

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declined to prosecute over 5,000 cases. Her predecessor pursued 89% of cases while Attorney Foxx pursued 84% of cases. They also found that Foxx's policy on felony shoplifting led to a decrease from 300 cases to around 70 cases per month.(2) Our work calls into question whether Attorney Foxx is truly fulfilling all of her promises as a progressive prosecutor, and who these changes are benefiting.

Data

Data acquisition. We acquire our data sets from Cook County Government Open Data [website](#). Although the Cook County Government provides data sets across all different sentencing stages (represented by different colors in Figure A.1), due to time and resource limitations, we will focus only on the intake and sentencing stages of the felony life cycle. We argue that these two stages comprise the main components of the upstream and downstream sentencing cycle – that is, where defendants are first taken into and taken out of the felony system, respectively. All data sets are downloaded from the website, and are exported into csv formats. Both data sets were first created on February 13th, 2018. For our analysis, we are using the latest version of both data sets—both of which were updated on September 19th, 2022.

Data Information. We are examining two periods in both data sets: the period before State Attorney Kim Foxx's entry and the period after State Attorney Kim Foxx's entry on December 1st, 2016. Both the intake and sentencing data sets are on the individual level with each row representing one individual's charge.

Limitations. The main limitation is that the intake data does not span as far back as the sentencing data. For each, there is still enough data to examine; however, the intake data begins 10 years after the sentencing data.

Methods

Data cleaning. Although the raw data sets have already been provided in tidy, tabular format, some columns still contain nonsensical observations due to inaccurate entries and/or other reasons. For that reason, we conduct a thorough cleaning process on the key columns that are important in our analysis. We use a similar cleaning process for both data sets, which includes the following steps: (1) cleaning the demographic characteristic columns; (2) cleaning the date-time sentencing columns; (3) cleaning the sentencing outcome columns; and (4) filtering to create analytic data sets. Each will be explained in below subsections.

Demographics columns. We start by cleaning up columns containing key demographic characteristics of defendants in both data sets. These columns include race (represented by column `RACE` in both data sets), gender (`GENDER`), and the defendant's age at the time of the incident (`AGE_AT_INCIDENT`). The race column initially contains granular categories of the defendant's race group, and in some cases, a mixture of several race groups. As our research aim is to investigate Attorney Foxx's impact on disparities between Black-white sentencing outcomes, we confine our analysis to defendants that belong to either Black or white race groups—we filter other race groups in the filtering subsection, which will be explained below. Black race group is defined as defendants belonging to either `Black` or `White/Black [Hispanic or Latino]` race categories. There was a code for `White [Hispanic or Latino]` leading us to believe that the majority of individuals categorized are Black and white biracial individuals. Further, we then define another column for indicating white defendants. White defendants are defined as defendants belonging to `White` or `CAUCASIAN` race groups. Lastly, in the original race group column, there were defendants belonging to other undefined race groups, such as `Albino`, `Biracial` or `Unknown`. We re-code these race groups as missing.

The next key characteristics column is the defendant's gender. The re-coding process for this field is relatively straightforward. In the initial `GENDER` column, there were several rows that could potentially correspond to a male sex in both the intake and sentencing data sets. These include 3 rows and 19 rows with `"Male name, no gender given"` in the sentencing and intake data sets, respectively. Although we acknowledge that this could correspond to a female gender, due to lack of available data points, we will assume a male gender for male names for the sake of simplicity. As with the race column, we re-code entries of unknown gender as missing, effectively excluding them from the analysis.

Lastly, we clean up the age column. Some of the entries in this column include nonsensical age values – e.g. more than 100 years of age and in some cases reaching up to 215. To address the issue of having these extreme outlier values, we employed winsorization method (3), where we truncate values above the 99.995th percentile to that percentile value. As a result, we end up with 81 years of age as our upper boundary. No such issue was found for the lower boundary of the age column.

Date-time columns. Our study analyzes changes in sentencing outcomes around a policy cutoff – that is, the entry of State Attorney Foxx in December 2016. As such, the time variable is a particularly important element in our analysis. We utilize different time variables in the intake and sentencing data sets, as each of these data sets entail different felony process of interest. In the intake data set, the main time variable is `FELONY_REVIEW_DATE`, which describes the date at which the defendant's felony review result was reached. Meanwhile, in the sentencing data set, the main time variable of interest is `SENTENCE_DATE`. This column describes the date at which a sentence was passed on the defendant. These columns were originally provided in different

formats; the `SENTENCE_DATE` column initially contained a time element (e.g. "12:00:00 AM"), while the felony review date column did not. As such, for the sentencing date column, the first thing that we do is to strip the hour element off the string column.

In both data sets, we observe errors in the date entries. For example, there were some rows containing year values that are above 2022, and even above 2100. We suspect that for the latter, the year was inaccurately typed into the system, inadvertently switching the third and the second digits of the year value. This would mean that the year 2019 will be recorded as 2109 due to such mistakes. We define a `regex` operation that cleans up these mistakes by using a list comprehension as shown by the code snippet below. After cleaning the date column, we convert the column into a `pandas` datetime object. We also extract the year, month, and day components out of the datetime column.

```
sentencing_cleaned['sentence_date'] = [re.sub(r'2[1-9]([0-9]+)', r'20\1', str(date))
                                         if bool(re.search(r'2[1-9]([0-9]+)', str(date)))
                                         else str(date)
                                         for date in sentencing_cleaned.sentence_date]
```

Next, we generate a `timedelta` object that would describe the time distance (measured in months, weeks or days) between the time variable of interest and our policy focus. Specifically, we create a `timedelta` variable that is defined as the time difference between State Attorney Foxx's entry into office (in December 2016) and the defendant's felony review date, or the defendant's sentencing date. The variable would take on a negative value if the date was earlier than the State Attorney's entry date, while positive values are for dates later than the entry date. In defining these `timedelta` variables, we have also created a centered running variable that will be used in the regression discontinuity in time approach, which will be discussed in the empirical strategy section.

Sentencing outcome columns. The next step would be to prepare our dependent or outcome variables for the estimation model. In our analysis, we focus on four outcome variables: (1) **probability of felony rejection**; (2) **probability of incarceration**; (3) **probability of being assigned into probation**; (4) **sentencing term**. The first variable measures outcome at the upstream stage, and is contained in the intake dataset. For that, we define an indicator variable that describes whether the defendant's felony review process ended as being rejected. Specifically, we consider the defendant's felony review result to be rejected if the original entry in the column is either `Rejected` or `Disregard`. Meanwhile, the second, third and last variables measure outcome at the downstream stage, and they are contained in the sentencing dataset. We follow [CCSAO's data glossary](#) and consider that a defendant is incarcerated if their `COMMITMENT_TYPE` is `Illinois Department of Correction`. Another sentence type is being assigned into probation; we consider a defendant to be assigned into probation if their `COMMITMENT_TYPE` contains the word "probation", as the original column contains various types of probation sentences. The last outcome variable is length of sentence term. The column is initially provided in a rather messy format, with different term units. We standardize these terms in days, before re-converting them to years (or months). However, in the process, we drop several entries with nonsensical term units such as `Term`, `Dollars`, `Pounds`, `Ounces` or `Kilos`.

Filtering to prepare analytic data set. As we finish up the cleaning process, we filter for several things to remove rows that will be excluded from our analysis of both data sets. In the intake data set, we found that there were observations with `FELONY_REVIEW_DATE` of later than 19 September 2022 (occurring in 2023 and 2024), which is not supposed to be possible. As such, we remove these rows from the analytic intake data set. For the sentencing data, we conduct a similar filtering process wherein we remove years that are above 2022. We also filtered against rows that contain zero commitment terms but contain non-null commitment units (e.g. 0 years, 0 months, among others). More importantly, on the sentencing data, we focus only on cases where only one participant is charged to avoid complications on plea bargains or informing from other participants that could also affect focal participants.

Empirical strategy. To estimate the impact of State Attorney Kim Foxx's entry on sentencing outcomes in Cook County, we implement a regression discontinuity in time (RDiT) approach. More specifically, in our setting, we use time as our running variable and State Attorney Kim Foxx's entry-1 December 2016-as the policy cutoff. We consider defendants who had their felonies reviewed and those who were sentenced after Kim Foxx assumed office as the treated units, while considering those who had their felonies reviewed or received sentencing before her tenure as the control units. We use a sharp RD methodology wherein we assume a sharp discontinuity in treatment probability after Kim Foxx's entry into office. In doing so, we rely on the `rdrobust` package proposed by Calonico et al (4). In our analysis, we aim to estimate the following local polynomial RD estimator of the following form:

$$\hat{\tau}_p(h_n) = \hat{\mu}_{+,p}(h_n) - \hat{\mu}_{-,p}(h_n) \quad [1]$$

with

$$\hat{\mu}_{+,p}(h_n) = \mathbf{e}'_0 \hat{\beta}_{+,p}(h_n) \text{ and } \hat{\mu}_{-,p}(h_n) = \mathbf{e}'_0 \hat{\beta}_{-,p}(h_n) \quad [2]$$

where h_n denote the selected optimal bandwidth, while $\hat{\mu}_{+,p}(h_n)$ and $\hat{\mu}_{-,p}(h_n)$ denote the intercept (around the time cutoff) of a weighted p -th order local polynomial regression for only the treated and control units, respectively. We use local linear

regression ($p = 1$) for the polynomial order and rely on `rdrobust`'s default bandwidth selection procedure and bias-corrected confidence intervals, both of which are detailed in Calonico et al (5).

Our identifying assumption is that observations located on both sides of the policy cutoff have sufficiently similar characteristics such that the only difference between the two observation groups are the treatment itself, that is, whether or not State Attorney Foxx had already assumed office. We then formally test the plausibility of this identifying assumption by testing whether there is a coexisting discontinuity in defendant characteristics around the policy cutoff. We conduct the test on the intake data, because the data represents the first stage at which defendants enter the felony life cycle system. On the other hand, we should expect discontinuity in characteristics to occur in the sentencing data set, had there been any significant changes to the felony review results (i.e. first stage sentencing processing) that aren't shared equally across population groups. Table 1 and Table 2 shows the estimated robust RD estimator of the discontinuity tests on defendant's characteristics and types of offenses being taken into the felony review system; we observe no significant jumps in either of these characteristics after Attorney Foxx assumed office.

Characteristics	Sample	Coefficients	Std. Err.	CI Lower	CI Upper	Left Obs.	Right Obs.	Bandwidth (Days)
Proportion of Black defendants	Full	0.005	0.010	-0.015	0.024	116630	93878	393.937
Age of defendants	Full	0.451	0.337	-0.209	1.111	113711	91611	382.035
	Black	0.485	0.342	-0.185	1.156	90537	78406	456.844
	White	-0.004	0.709	-1.393	1.386	23174	13205	496.046
Proportion of female defendants	Full	-0.006	0.009	-0.023	0.010	116630	93878	483.111
	Black	-0.006	0.009	-0.024	0.012	92921	80250	479.305
	White	-0.002	0.020	-0.042	0.038	23709	13628	573.649

Table 1. We observe no discontinuities in defendant characteristics post Attorney Foxx's entry

Offense Type	Sample	Coefficients	Std. Err.	CI Lower	CI Upper	Left Obs.	Right Obs.	Bandwidth (Days)
Narcotics	Full	0.004	0.003	-0.001	0.009	116630	93878	571.094
	Black	0.003	0.003	-0.003	0.009	92921	80250	546.301
	White	0.008	0.005	-0.003	0.018	23709	13628	557.354
Unlawful Use of Weapon	Full	0.001	0.012	-0.024	0.025	116630	93878	231.874
	Black	-0.001	0.014	-0.030	0.027	92921	80250	241.798
	White	0.010	0.012	-0.014	0.035	23709	13628	436.062
Retail Theft	Full	-0.006	0.011	-0.028	0.016	116630	93878	278.254
	Black	-0.009	0.011	-0.031	0.013	92921	80250	336.348
	White	-0.001	0.027	-0.053	0.051	23709	13628	310.436
Burglary	Full	0.001	0.005	-0.008	0.010	116630	93878	602.595
	Black	-0.006	0.005	-0.015	0.003	92921	80250	558.770
	White	0.024	0.014	-0.004	0.052	23709	13628	508.286
Aggravated DUI	Full	-0.003	0.005	-0.012	0.006	116630	93878	515.350
	Black	-0.002	0.005	-0.012	0.007	92921	80250	491.637
	White	-0.000	0.012	-0.024	0.024	23709	13628	782.856

Table 2. We also observe no discontinuities in types of crimes being committed after Attorney Foxx's entry into office

Results

In this section, we present the results of our analysis. We will first outline several key findings from descriptive analysis of both the intake and sentencing data sets. In the last subsection, we cover the regression results pertaining to each of the four outcome variables that have been listed in the previous section.

Descriptive statistics. After our data cleaning and filtering, we had 369,399 observations in intake and 150,245 observations for sentencing. Table 3 shows the distribution of defendant sex and race across both the intake and sentencing data sets. In the former, 86 percent of defendants are male, while it is 87 percent in the latter data. Our tabulation also suggests that around 82 percent of defendants in both intake and sentencing data are Black defendants. Altogether, these tabulations suggest that both data have similar characteristics in terms of defendant's sex and race characteristics.

Next, we investigate differences in defendant age distribution across race groups in both data sets. A summary statistics of both data sets is presented in Table 4. The tabulation suggests that across the two data sets, both Black and white defendants

Characteristics	Level	Intake		Sentencing	
		N	Proportion	N	Proportion
Sex	Male	317431	0.860	130108	0.866
	Female	51738	0.140	20137	0.134
Race	Black	303727	0.822	122898	0.818
	White	65672	0.178	27347	0.182

Table 3. Both intake and sentencing datasets have similar defendant's sex and race characteristics

have largely similar age distribution – as indicated by the same minimum and maximum age values. However, a comparison of the median and mean age of white and Black defendants does seem to indicate that white defendants are slightly older than Black defendants. The median ages for white defendants in the intake and sentencing data are 32 and 33, respectively, while for Black defendants the same values are 31 and 29, respectively.

	Intake						Sentencing					
	Min	P25	P50	Mean	P75	Max	Min	P25	P50	Mean	P75	Max
Race												
White	17.0	25.0	32.0	34.60	42.0	81.0	17.0	25.0	33.0	34.76	43.0	81.0
Black	17.0	23.0	31.0	34.09	44.0	81.0	17.0	22.0	29.0	32.71	42.0	81.0

Table 4. Across the two data sets, white defendants are somewhat older than Black defendants

We then tabulate each of the four sentencing outcome variables in our analysis, i.e. the proportion of rejected felonies, the proportion of incarcerated defendants, the proportion of defendants assigned to probation sentences, and the length of sentence terms. Table 5 presents the by-race tabulation of these outcome variables. The data suggests that Black defendants are less likely to have their felonies rejected. 6.9 percent of white defendants' felonies are rejected in the felony review process, while around 6.6 percent of Black defendant's felonies are rejected. Black defendants are also more likely to receive incarceration sentencing; while around 39 percent of white defendants are incarcerated, more than half (57 percent) of Black defendants are incarcerated. Also, Black defendants in our data receive longer sentence terms than their white counterparts. While the average sentence term for Black defendants is around 3.16 years, the average for white defendants is only around 2.6 years.

Race Group	Prop. rejected felonies	Prop. on probation	Prop. incarcerated	Sentencing term (years)
Full	0.066	0.388	0.538	3.058
White	0.069	0.517	0.388	2.616
Black	0.066	0.359	0.572	3.156

Table 5. Black defendants are more likely to be incarcerated and sentenced longer than their white counterparts

Further, we visualize the trend of each of these outcome variables by year and break down these trends by race groups in Figure 1. We also add the vertical reference line in 2017, indicating the period of Attorney Foxx's entry into office in December 2016. From the figure, one can observe a significant jump in the likelihood of rejected felonies after Attorney Foxx assumed office. This is consistent with the State Attorney's policy on moving away from prosecuting low-level shoplifting and drug offenses*. Interestingly, the figure also suggests that the Black-white gap in felony rejection has widened after Attorney Foxx began her tenure, which could be attributable to the difference in types of offenses committed by defendants of different race groups. Further, one can also infer from the figure that Black defendants experienced higher likelihoods of receiving probation. This could also reflect the State Attorney Kim Foxx's policy on promoting alternative sentencing programs for low-level offenses, such as the diversion program. Meanwhile, although not as apparent as the change in felony rejection rate, incarceration rate also seems to decrease at a faster rate after the State Attorney's entry into office. Lastly, the graph suggests no obvious changes in sentence lengths, both among Black and white defendants.

Regression analysis.

* See the following <https://www.themarshallproject.org/2019/10/24/the-kim-foxx-effect-how-prosecutions-have-changed-in-cook-county>

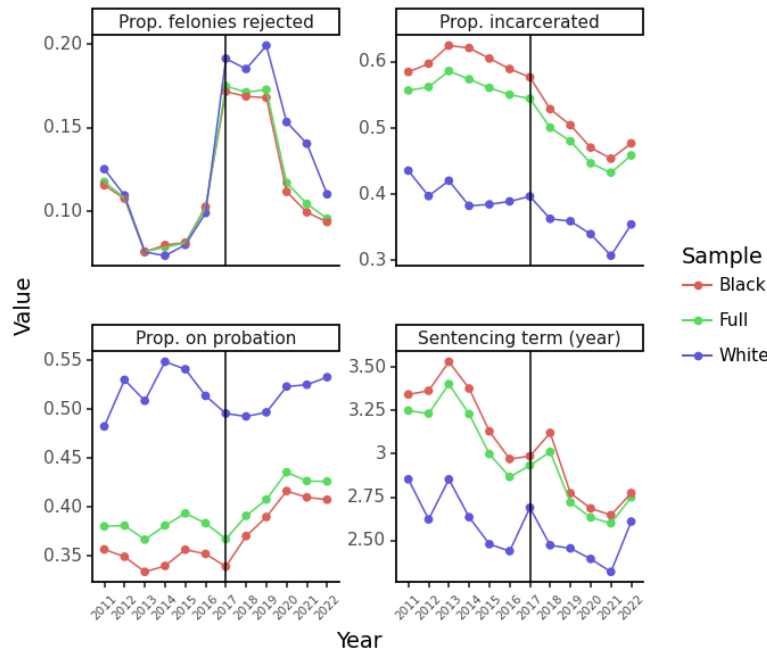


Fig. 1. Strong jumps in the proportion of felonies rejected are observed, particularly among white defendants.

Proportion of felonies rejected. We first consider the outcome variable at the first stage of the felony life cycle, the outcome of the felony review result. Figure 2 shows the discontinuity plot on the probability of felony rejection of all Black and white defendants shortly before and after Attorney Foxx's tenure; the model chooses 407 days before and after her tenure as the comparison bandwidth. Consistent with the result presented in the descriptive analysis section, the graph suggests a significant discontinuity after Attorney Foxx's entry into office in December 2016. Further, Figure 3 plots the by-race breakdown of the three regression discontinuity estimates proposed by Calonico et al (4): (1) Conventional, (2) Bias-Corrected; and (3) Robust estimates, of which our preferred estimate is the third option. Also consistent with the descriptive results, we find that white defendants experienced stronger, upward discontinuity in the likelihood of felony rejection as compared to Black defendants. White defendants experienced a 12.7 pp increase in felony rejection rates, while Black defendants only experienced a 7.2 pp increase. As a result, the Black-white felony rejection gap has widened post-Attorney Foxx's entry into office (see Figure A.2 of the Appendix section). In addition, Figure A.3 also shows that the increase in felony rejection rates is largely driven by increases in the rejection rates among retail theft and narcotics offenses, which experienced increases of about 32.6 pp and 18.5 pp, respectively.

Likelihood of incarceration. We then consider the next outcome in the felony life cycle stage, which is the likelihood of incarceration. Figure 4 displays the discontinuity plots in the overall likelihood of being incarcerated. By comparing outcomes in the 282 days leading to and after Attorney Foxx's tenure, we observe a significant, lower discontinuity in the likelihood of incarceration among all defendants, albeit at a much smaller rate (6.8 pp) compared to changes in the likelihood of felony rejection (18.5 pp). Most of these changes are attributable to decreases in retail theft incarceration (see Figure A.4). Figure 5 further shows the by-race breakdown of Attorney Foxx's impact on incarceration rates; our findings suggest that both Black and white defendants experienced a rather similar reduction in incarceration rates – 5.3 pp and 6.1 pp, respectively. This implies that although Attorney Foxx's entry did lead to reductions in incarceration rates, it did not lead to significant changes in racial incarceration gaps.

Likelihood of probation. We then consider the other type of sentencing outcome, the likelihood of being sentenced into probation. Figure 6 shows the discontinuity plot of overall likelihood of being assigned into probation sentencing. By using data from 500 days before and after Attorney Foxx entered office as the comparison bandwidth, we find that Kim Foxx's entry had no impact on the likelihood of being assigned into probation. While her tenure did cause the prevalence of probation assignment to slightly decline by 0.87 pp, our estimation suggests that the effect is not statistically significant. However, looking at the overall effect masks the heterogeneity in effects across offense types. Further, Figure 7 plots the by-race breakdown of the effects on probation rates; we find that Attorney Foxx's entry did not cause probation rates to significantly change among both Black and white defendants, although white defendants did experience slightly higher decrease in the probation likelihood as compared to Black defendants. While the overall effect is insignificant, we find indications that there is a strong decrease in likelihood of probation among retail theft offenses, which virtually removes pre-existing gaps in retail theft probation rates between Black and white defendants (see Figure A.5).

RD Plot: Foxx's Entry and Proportion of Felonies Rejected

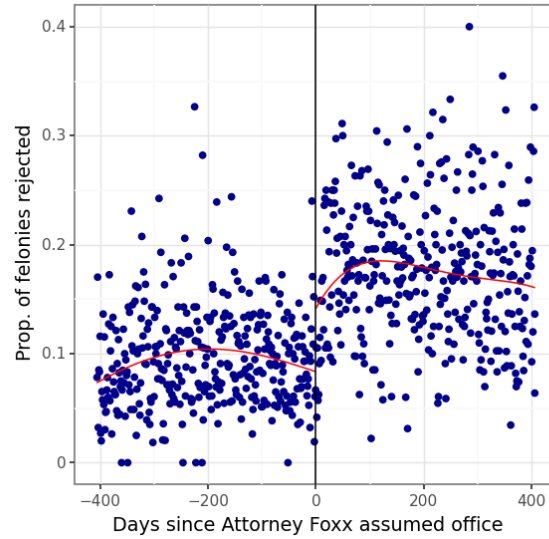


Fig. 2. After Kim Foxx entered office, the proportion of felonies rejected experienced a significant jump.

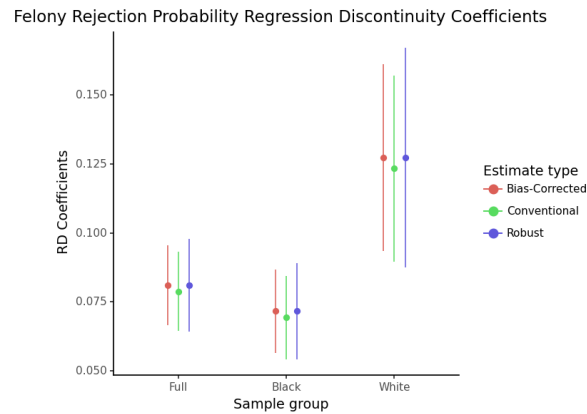


Fig. 3. White defendants experienced higher increases in probability of felony rejection upon Attorney Foxx's entry.

212

213 **Sentencing term.** Lastly, we consider the State Attorney's impact on the length of sentence terms. Figure 8 visualizes the
 214 discontinuity in sentence days 432 days leading to and after Attorney Foxx took office. Our estimates show that Attorney
 215 Foxx's tenure had no impact on overall sentence lengths; although our estimate shows that sentence lengths did decrease by
 216 around 46 days following her entry, such effect is not statistically distinguishable from zero. The by-race breakdown of the RD
 217 estimate, as shown by Figure 8, also shows no heterogeneity in effects across Black and white defendants, with Attorney Foxx's
 218 entry having null effects on the sentence terms of both Black and white defendants—although we do observe significant length
 219 drops among female Black defendants (see Figure A.6). This means that virtually Attorney Foxx's entry did not lead to any
 220 changes in racial gaps in sentencing lengths.

221

222 Discussion

223 The results of our analysis above show that while Kim Foxx's tenure as Cook County State's Attorney has reduced the number
 224 of cases prosecuted, the reform mechanisms themselves have associated racial disparities, especially in the realm of felony
 225 rejections, where Foxx's own reforms created a racial disparity that did not previously exist.

226

227 While current results suggest that Foxx's implementation of reforms has created and maintained racial disparities, several
 228 robustness checks are needed to test results. Hausman and Rapson (2018) recommends several such tests, including placebo
 229 tests, "donut" regression discontinuity, and autoregression tests.(6) In future iterations of this study, we will include such
 230 robustness checks. Another limitation of this study is that our model simplifies the felony sentencing process. Cook County

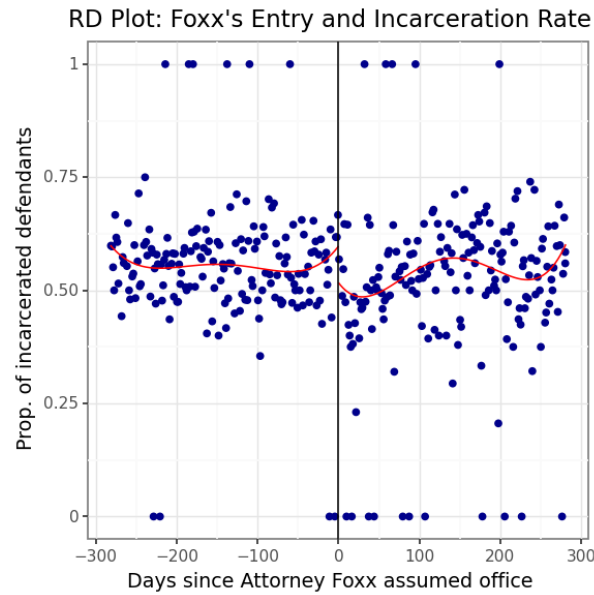


Fig. 4. Incarceration rate slightly dropped upon Kim Foxx's entry into office.

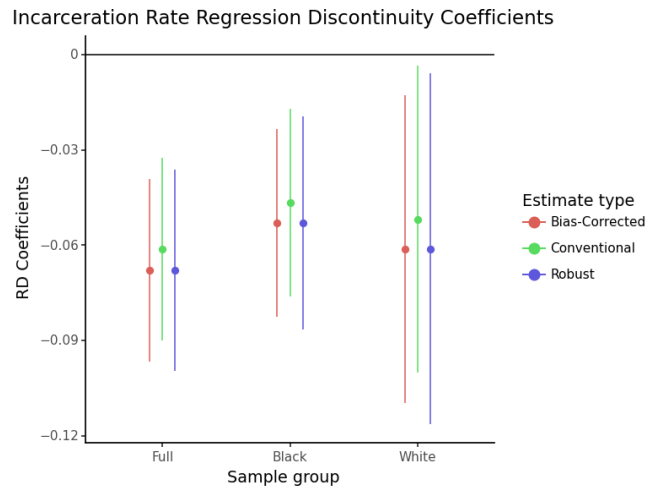


Fig. 5. Black and white defendants experienced relatively similar drops in likelihood of incarceration

offers data on five stages of the process, but our study analyzes two of these five stages. Future work could apply a similar method of analysis to data on the other three stages.

Despite limitations, the regression discontinuity in time method is a powerful method for testing the effects of an event – in this case Foxx's entry into office – as a "treatment." Further work can refine the analysis in this paper. Additionally, this same method can be applied to data from other cities with progressive prosecutors as part of a larger project to assess the extent to which these prosecutors fulfill their mandate to end racial disparities in the American carceral system.

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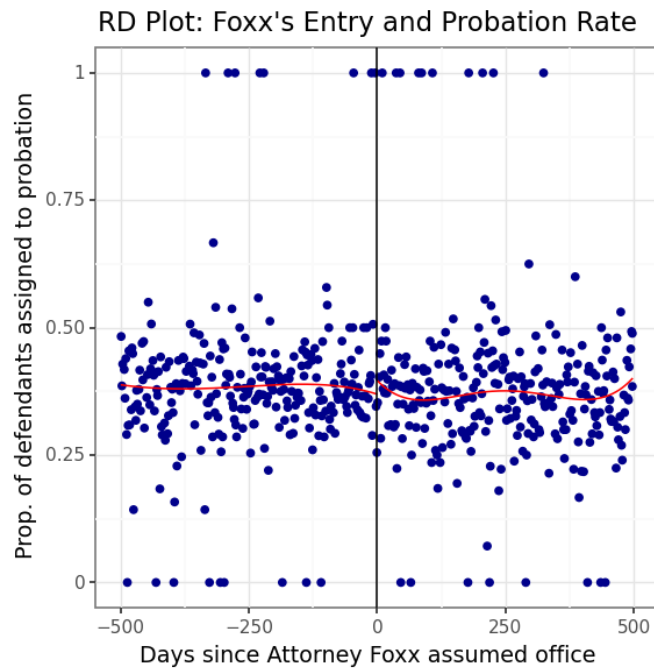


Fig. 6. Probation rate did not change after Kim Foxx's entry into office.

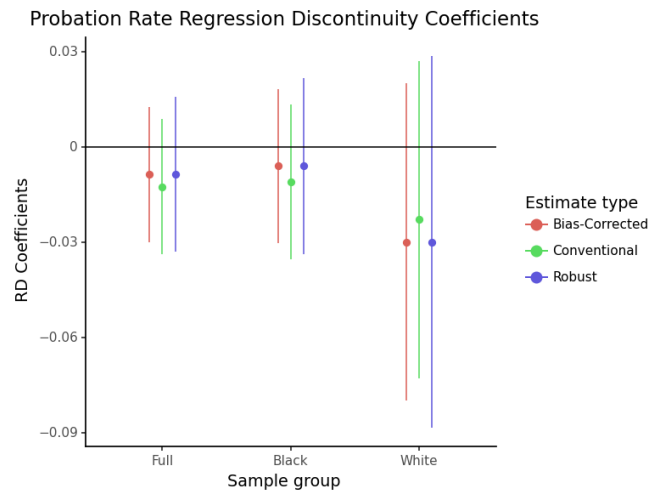


Fig. 7. White defendants experienced slightly higher decrease in the likelihood of being assigned into probation after Kim Foxx assumed office.

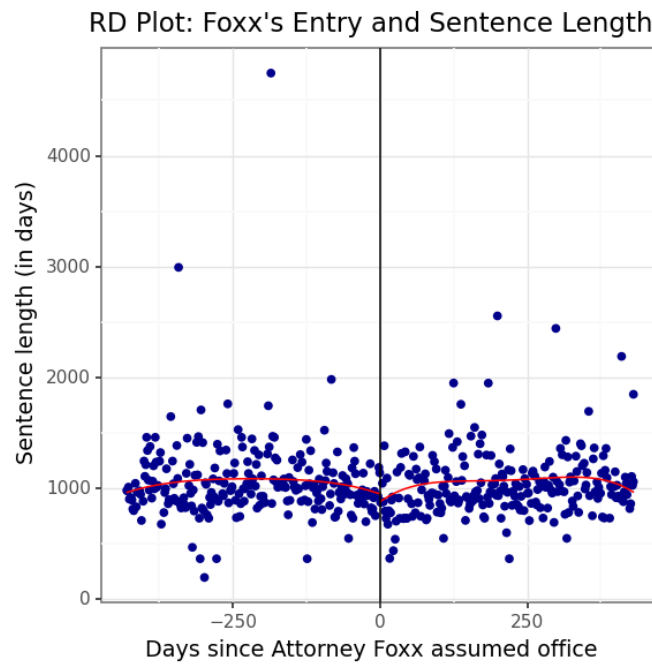


Fig. 8. Length of sentence terms also did not change after Kim Foxx's entry into office.

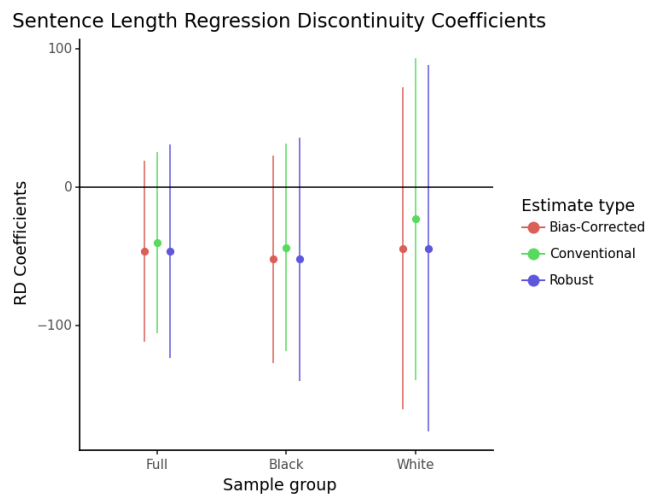


Fig. 9. There were no significant variations between Black and white defendants in terms of Kim Foxx's impacts on sentence lengths.

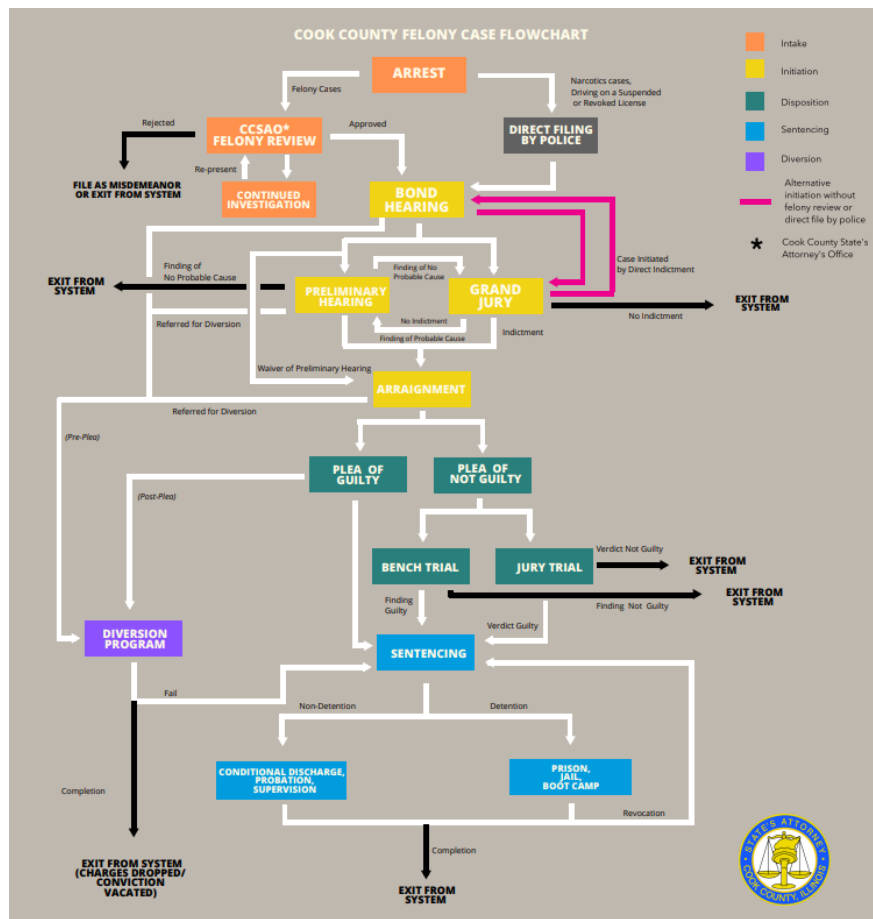


Fig. A.1. Felony Case Life Cycle

Proportion of Rejected Felonies Before/After Kim Foxx, by Race

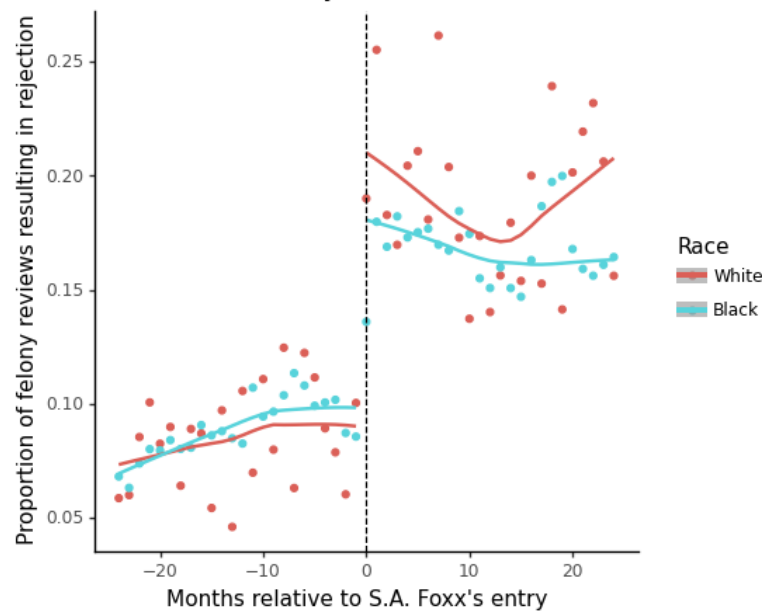


Fig. A.2. Black-white gaps in the likelihood of experiencing felony rejections widened after Attorney Kim Foxx assumed office.

Felony Rejection Probability Regression Discontinuity Coefficients

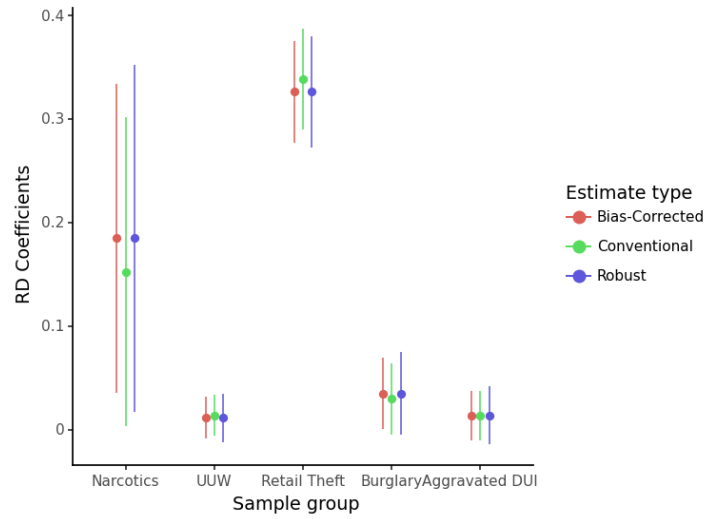


Fig. A.3. Retail theft and narcotics offenses experienced the largest increases in felony rejection post-Attorney Foxx's entry into office

Incarceration Rate Before/After Kim Foxx's Entry, by Offense Groups

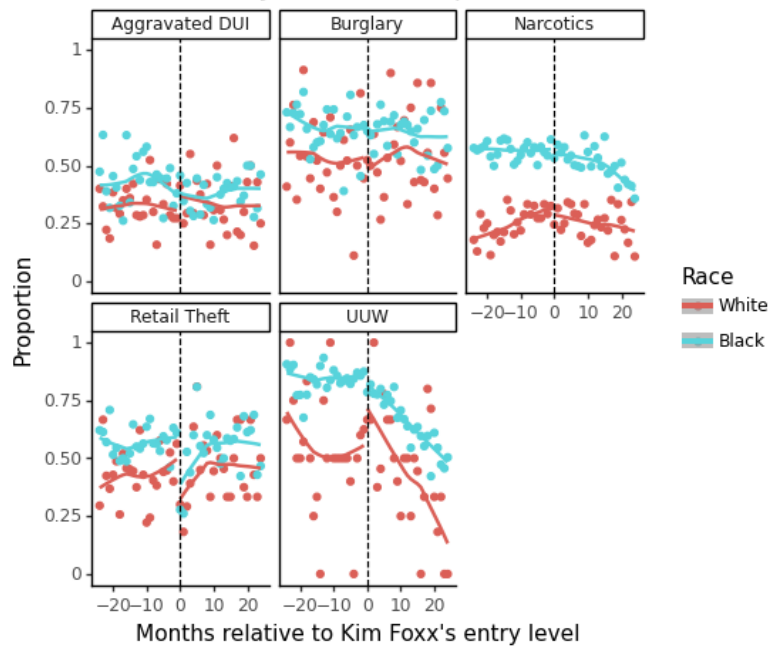


Fig. A.4. Retail theft defendants experienced the largest decreases in incarceration likelihood

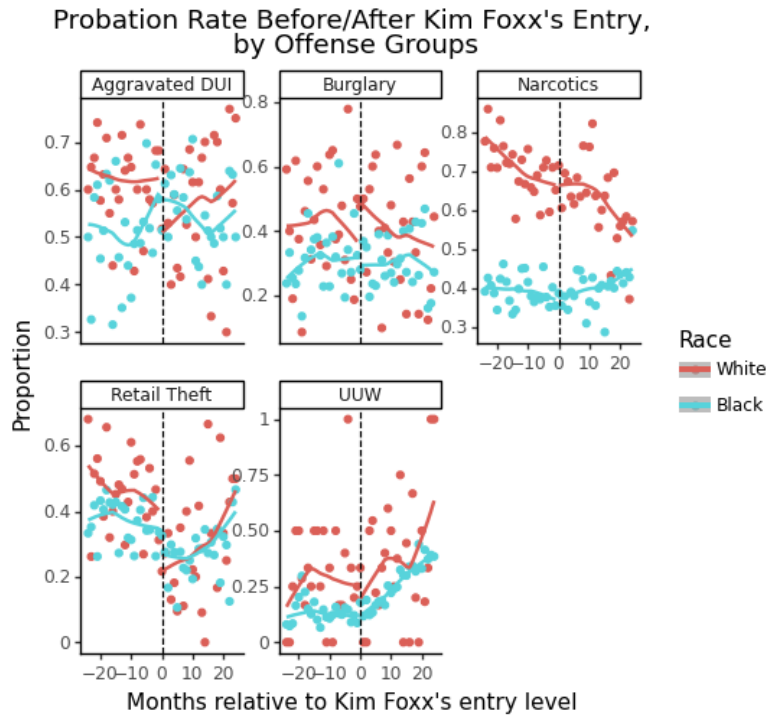


Fig. A.5. White theft defendants experienced the largest decreases in likelihood of probation

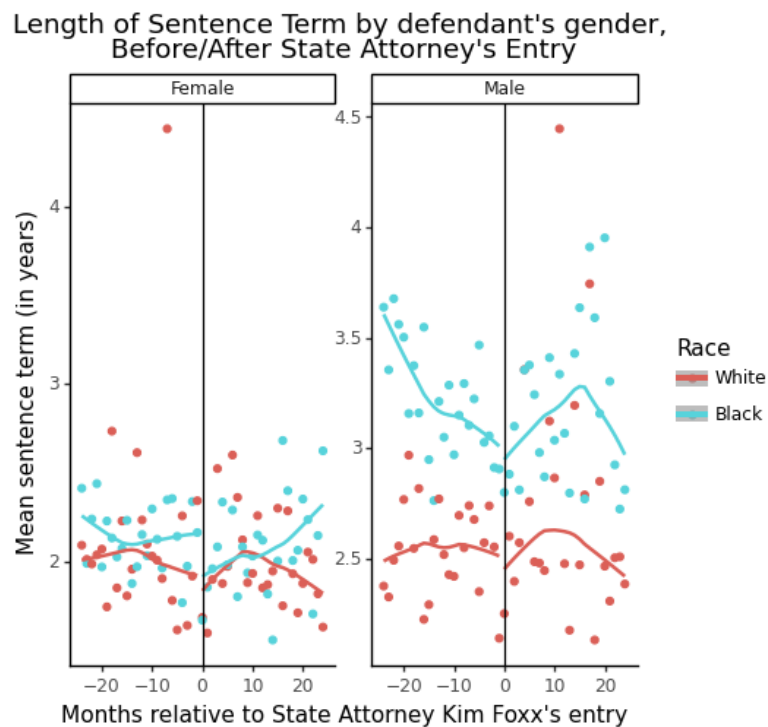


Fig. A.6. Female Black defendants experienced a larger drop in sentence lengths after Attorney Foxx's entry into office.