The Impact of Jail Reduction Strategies on Community Safety

Findings from Two
Safety and Justice Challenge Sites

by Fred Butcher, Amanda B. Cissner, and Elise Jensen

Center for Justice Innovation

SAFETY + JUSTICE CHALLENGE

The Impact of Jail Reduction Strategies on Community Safety: Findings from Two Safety &
Justice Challenge Sites

By Fred Butcher, Amanda B. Cissner, and Elise Jensen

© January 2026

The Impact of Jail Reduction Strategies on Community Safety: Findings from Two Safety and Justice Challenge Sites

Fred Butcher, Amanda B. Cissner, and Elise Jensen

Executive Summary

The John D. and Catherine T. MacArthur Foundation launched the Safety and Justice Challenge (SJC) in 2015 with the goal of safely reducing jail populations in the selected SJC sites across the country. Toward this end, SJC sites have implemented numerous strategies, including diversion, enhanced review of those detained in jails, bail reform, tools to inform decision making, improved treatment options, re-entry strategies, and others. A growing body of evidence suggests that many sites have successfully reduced jail populations without risk to community safety.

In their efforts to reduce reliance on incarceration without endangering the public, two SJC sites (New Orleans, LA and Lucas County, OH) implemented a range of reforms, including validated risk assessment (the Public Safety Assessment or PSA), diversion programs, pretrial detention alternatives, and expanded treatment options. This study examined whether the jail reduction strategies implemented in these two SJC sites reduced jail populations *without* increasing crime or sacrificing community safety. To assess the impacts of SJC strategies, we compared official records on jail bookings across three study periods: a pre-implementation period prior to the SJC rollout and two post-implementation periods. This strategy allowed us to avoid erroneously attributing jail reductions necessitated by the COVID-19 pandemic to the SJC strategies.

Key Takeaways

- **Incarceration can be avoided without negatively impacting public safety.** We found that implementation of SJC strategies was followed by declining jail bookings *without* an increase in crime.

- **In fact, recidivism rates generally decreased** following the implementation of SJC strategies in both sites, including felony and violent recidivism**.**

- **Less time spent in jail means greater public safety.** Our results show that shorter jail stays were associated with lower recidivism risk. By limiting the time individuals spend in jail, it may be possible for sites to reduce recidivism. In both sites, the proportion of individuals who spent *no time* in jail on the initial case increased over the life of the SJC initiative.

- **Racial disparities in jail bookings persisted.** While booking trends declined among both white and BIPOC[1] individuals throughout the study period, bookings were twice as likely to involve BIPOC individuals than white individuals in both sites.

Predicted Probability of Recidivism at 1 Year, by Charge Type and Site
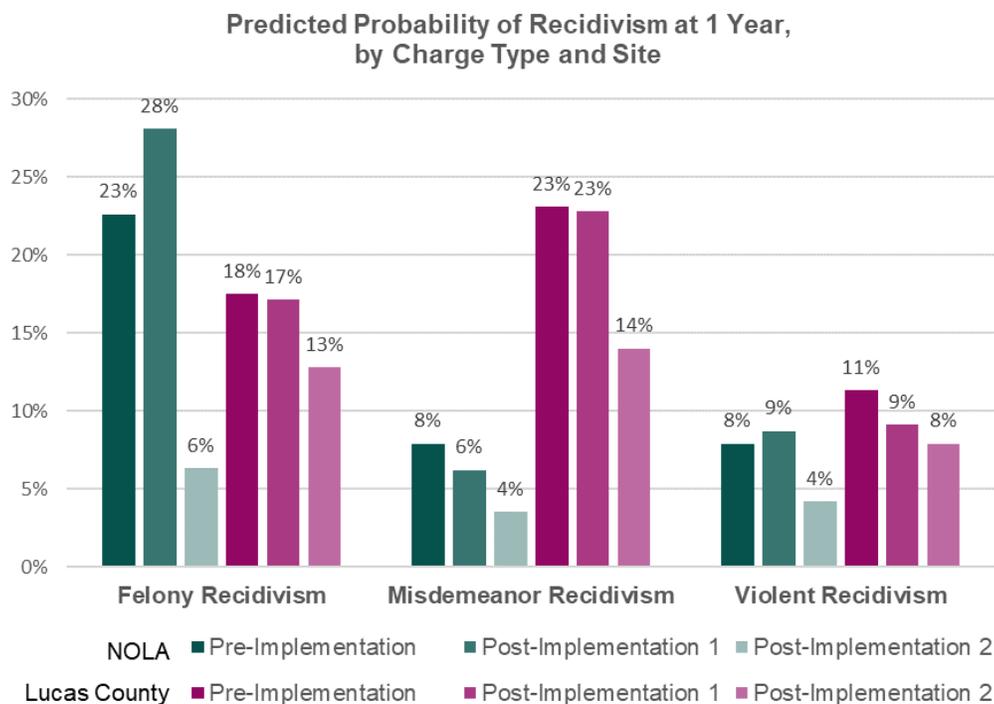
Conclusion

In general, our findings suggest that jurisdictions can safely decrease jail populations without undermining community safety. Despite rhetoric linking the criminal justice reforms of recent years to crime spikes—real or imagined—this study found no evidence that the jail reduction reforms adopted in these sites led to increases in crime. In fact, the findings show *less* recidivism in the post-reform periods across all charge levels.

Racial disparities persisted in these sites even as bookings overall declined. This finding aligns with previous research on SJC strategies that has shown that adopting strategies that successfully cut the number of people in jail does not *necessarily* eliminate racial disparities—in some cases,

---

[1] Black, Indigenous, and People of Color.

such efforts have even exacerbated disparities. Jurisdictions must intentionally develop strategies targeting these disparities.

Minimizing the unnecessary use of jail can make communities safer. Those individuals who were released earlier (or not held in jail at all) were less likely to recidivate. A validated risk assessment provides one means of supporting decision makers in making informed decisions about conscientious use of detention, setting bail, and appropriate supervision and service connections. These tools can help jurisdictions prioritize who remains in custody while moving to reduce jail populations overall. The strategies implemented in these sites (including decision making informed by a validated risk assessment tool) reduced the use of jail without endangering public safety.

Acknowledgements

Table of Contents

Chapter 1
Introduction

The John D. and Catherine T. MacArthur Foundation launched the Safety and Justice Challenge (SJC) in 2015 with the goals of safely reducing jail populations and addressing the disparate impacts of over-incarceration on communities of color. Toward these ends, the now-57 SJC sites across the country have implemented numerous strategies, including diversion, enhanced review of those detained in jails, bail reform, tools to inform decision making, improved treatment options, re-entry strategies, and others. A growing body of evidence points to the fact that many sites have successfully reduced jail populations without risk to community safety.[1]

Despite these generally positive findings, conversations around jail reduction have shifted in recent years as critics began to suggest that such reforms may have played a role in rising rates of violent crime observed across the country in the period immediately following the COVID-19 pandemic. While all crime—and violent crime specifically—has decreased in the intervening years since 2020-2021,[2] such concerns continue to shape national conversations around violent crime and public safety.

The current study examines whether the strategies implemented in two SJC sites (New Orleans, LA and Lucas County, OH) have managed to reduce jail populations *without* sacrificing community safety. In particular, despite some increases in specific violent crimes in both sites in the immediate aftermath of the COVID-19 pandemic (circa 2020-2021) and declining jail populations, we explore whether several measures of community safety remain stable. The study seeks to answer the following research questions:

1. **Booking Trends:** Did the types of incidents that led to a jail booking look different over time? How did the populations booked into jail change from the period before the SJC reforms to the post-implementation period? Were there changes in the types of charges (e.g., severity, type) and individual characteristics (e.g., race, criminal history) among those booked?

2. **Crime Rates:** How did crime rates overall change from the period before the SJC reforms to the post-implementation periods?

3. **Recidivism Trends:** Did repeat returns to jail increase or decrease over time? Were there changes in recidivism from the period before the SJC reforms to the post-implementation period? Specifically, were there changes in new bookings on any charge, felony charges, or violent charges over this period? Did trends in recidivism differ based on personal or case characteristics (e.g., by demographics, criminal history)?

4. **Criminal Trajectory:** Did individuals increase (or decrease) in the severity or number of criminal charges over time? Regardless of changes in rates of recidivism, were there changes in the criminal trajectory among those with a new booking incident? Did the amount of time to a new booking differ? Were there identifiable subgroups of individuals based on criminal history and, if so, are there differences in recidivism for these groups?

This chapter continues with an overview of the two study sites, including SJC implementation and strategies and a description of the populations booked in those sites from just prior to the SJC kick-off through a post-COVID-19 period. Chapter 2 presents the results of time series analyses, examining the booking trends across the two sites, including breakouts by type of offense (violent or nonviolent) and by the race of booked individuals. Chapters 3 through 5 present findings from the recidivism analyses, including logistic regression examining predictors of felony, misdemeanor, and violent re-arrest (Chapter 3); survival analysis looking at time to a new arrest (Chapter 4); and latent class analysis looking at whether there are identifiable re-offense profiles (Chapter 5). Finally, Chapter 6 concludes with key takeaways, discussion, and study limitations.

The Study Sites

The study sites applied a broad array of strategies, some of which were similar across the two sites and some of which were unique. The Public Safety Assessment (PSA) was a central component of each sites' SJC work. The PSA is a validated actuarial risk assessment tool intended to inform pretrial decision making. The tool is scored to predict three pretrial outcomes: failure to appear, new criminal arrest, and new violent criminal arrest. Scores are based on age, current arrest characteristics, criminal history, and prior failures to appear.[3]

New Orleans, Louisiana (Orleans Parish) was one of the original 2015 SJC sites. In 2015, the state legislature established the Louisiana Justice Reinvestment Taskforce, which issued recommendations aimed at reducing the state's prison population. The resultant Justice Reinvestment Package was signed into law in 2017.[4] The site adopted the PSA as one strategy to reduce pretrial jail populations in 2018, alongside other statewide efforts. Other SJC strategies implemented in New Orleans include police-led diversion for individuals facing issues related to mental illness, substance use, and/or other social challenges; strategies for addressing racial disparities in the criminal legal system, including a racial disparity working group and collecting and analyzing data to identify disparity drivers; a community engagement advisory group; and a program to increase access to defense counsel at first court appearance.[5] Average daily jail populations (ADPs) are 17% lower now than they were at the start of SJC implementation, though they have been trending up since a low in mid-2021.

Lucas County, Ohio was also one of the initial 2015 SJC sites.[6] Prior to the formal SJC launch, in 2015, a federal judge mandated the site to adopt a jail management plan to reduce jail crowding. The jurisdiction had already been subject to a federal consent decree with a focus on

decreasing pretrial jail populations since 1976.[7] Over the intervening years, the county continued to struggle to reduce jail overcrowding,[8] with earlier strategies focusing on pretrial release of those facing specific charges (e.g., nonviolent misdemeanors).

After a jail population study was completed in 2014,[9] the site shifted to a strategy focused on pretrial release informed by risk and ultimately adopted the PSA to inform risk-based decision making in 2015. By using a formalized risk assessment tool, the site sought to identify for release those who pose the lowest risk to public safety—i.e., those least likely to be arrested for a new offense if released into the community. In addition, the PSA has the potential to improve return to court rates and reduce warrants for nonappearance, as the tool also includes a failure to appear score.

Other strategies implemented in Lucas County include diversion for individuals with mental health and/or substance use issues, enhanced training for system stakeholders, targeted review of jail populations to identify those who might safely be released or whose cases could be resolved quickly, mechanisms for connecting system-involved individuals to service providers expeditiously, improved coordination and communication between community corrections agencies, and a working group dedicated to advancing racial equity in the criminal legal system.[5] According to ADP statistics tracked through the initiative, Lucas County has reduced ADPs more than 45% since implementing the PSA.

The Study Sample

This study includes three distinct samples in both sites: a pre-implementation sample prior to the SJC rollout and two post-implementation periods. We decided on this sampling strategy for several reasons: 1) to allow the program sufficient time to be fully operational and avoid drawing conclusions from a time when the SJC strategies were still being rolled out, we excluded the initial year of implementation—a *hiatus* period—meaning the first post-implementation sample begins after the start of the SJC implementation (2018 in New Orleans; 2016 in Lucas County); 2) to avoid the timeframe most impacted by the COVID-19 pandemic in our analyses, with the knowledge that COVID-19 precipitated changes in jail populations that had nothing to do with SJC strategies; 3) to create a more robust post-implementation period including multiple time points; 4) to ensure the pre-implementation and post-implementation samples would cover a comparable period of time (i.e., 12 months per sample); and 5) to allow for two years of criminal history and a minimum of one year of recidivism follow-up for all samples. Table 1.1 presents the sampling timeframes for both sites.

The full samples include only misdemeanor- or felony-level charges. We excluded lower-level traffic infractions and citation-only charges.[10,11] The New Orleans sample includes a total of 20,074 individuals booked into New Orleans jail across the sampling years.[12] For Lucas County, the total sample includes 34,137 booked individuals across the sampling years.[13]

Rather than analyzing the entire booked population in New Orleans and Lucas County, which was far larger than necessary to perceive significant differences between populations, we selected a random subsample of individuals across the three study periods using 1:1 nearest neighbor matching without replacement to select individuals based on race, age, gender, and prior felony booking in the 2 years prior to the initial booking. This resulted in a total study sample of 2,660 in New Orleans and a total study sample of 2,798 in Lucas County.

Table 1.1. Sampling Timeframe and Sample Size by Site

		NOLA	Lucas
	N	2,660	2,798
Pre-Implementation		2017 n = 892	2015 n = 930
Hiatus (strategies get up and running; not included in sampling)		2018	2016
Post-Implementation 1, Early Implementation		2019 n = 873	2017 n = 936
COVID-19 (not included in sampling)		2020	2020
Post-Implementation 2, Late Implementation		2021 n = 895	2022 n = 932

Booking Trends

To answer our first research question, we examined differences between the full pre- and post-implementation samples in both sites.[14] For this purpose, we drew from the entire sample rather than the reduced subsample described above, with the reasoning that we wanted to document the full array of cases booked in the sites. Full results are presented in tables as Appendix A.

New Orleans

Overall, the number of individuals booked into a New Orleans jail dropped substantially from the pre-implementation period to post-implementation period 1 and even more so in post-implementation period 2. The second set of declines coincided with the COVID-19 pandemic, when arrests were at an all-time low due to the lockdown, and subsequent slow return to normal operations. The three samples are similar in terms of both demographics and severity of initial booking charges (i.e., misdemeanor or felony).[15] Although there are few differences in the *types* of charges on which individuals were booked, the post-implementation 2 sample shows significantly more person-related bookings (36% pre-implementation, 39% post-implementation 1, 52% post-implementation 2) and fewer drug-related bookings (19% vs. 20% vs. 9%). Despite these statistical significances, the effect sizes indicate only minimal associations.

Regarding disposition outcomes, release on recognizance remains relatively stable; the post-implementation 2 sample experienced a sharp increase in the use of bail bonds (39% vs. 32% vs. 61%), but fewer bookings where no action was taken—meaning the state decided to not formally charge and prosecute the case. While the difference between the dispositions is statistically significant, the effect size remains low.

Finally, the samples show minimal differences in the criminal histories of those booked. The post-implementation samples exhibit a slightly higher incidence of *any* prior bookings (24% vs. 29% vs. 27%). The percent of those with prior bookings by charge type remains unchanged across the periods (around 13%-16% for violent arrests, around 22%-26% for felonies, and 17% up to 24% for misdemeanors).

Lucas County

Similar to the findings from New Orleans, the number of bookings in Lucas County dropped substantially from the pre-implementation period; from 2015 to 2022, the number of bookings fell 37%. While there were only small differences in the types of charges for which an individual was booked over the full study period, the proportion of individuals who were booked for a drug charge dropped from 15% in the pre-implementation period to 10% in the post-implementation 2 period. During this time, the proportion of bookings for a violent charge climbed (34% pre- vs. 40% post-1 vs. 41% post-2), along with a small decline in the proportion of bookings for misdemeanors (66% pre- vs. 60% post-1 vs. 59% post-2). Bookings for felony charges also increased from the pre- to post-implementation periods (34% pre- vs. 40% post-1 vs. 41% post-2).

Generally, the proportion of the post-implementation 2 population with a criminal history is lower for most of the measures we examined. However, it is important to view these numbers with caution as two-year criminal history of the 2022 post-implementation 2 cohort includes the COVID-19 period, where arrests and bookings were generally down.

Key Takeaways, Booking Trends

There were several small but statistically significant findings of note across the sites. From the pre- to post-implementation 2 periods:

Table 1.2. Changes in Booking Trends, Pre- to Post-Implementation 2

	NOLA	Lucas
Change in proportion of individuals booked on a **felony charge**	up 1%	up 7%
Change in proportion of individuals booked on a **violent charge**	up 12%	up 9%
Change in proportion of individuals booked with a **prior felony charge**[16]	up 2%	up 1%

Taken together, these findings suggest that bookings involved more serious current charges as well as a more serious criminal history following SJC implementation in both Lucas County and New Orleans. Given that the two sites used a PSA risk assessment as one approach to reducing

jail populations, we would expect that individuals with lower-level charges would be the most likely to be diverted from the justice system. That is, those individuals facing less serious charges (i.e., nonviolent and misdemeanor charges) and those without a history of felonies were less likely to be booked—possibly less likely to be arrested altogether and/or more likely to be released without being booked—in the post-implementation periods. These findings along with an overall decline in the number of new jail bookings over the three time periods demonstrate an impact of the interventions in both study sites.

In New Orleans, booking dispositions[17] saw a dramatic increase in the use of bail bonds from the pre- and post-implementation 1 phases to the post-implementation 2 phase. At the same time, the proportion of individuals who were sentenced or held (not released) decreased, suggesting that the SJC strategies were successful in keeping people out of jail.

Despite these significant findings, it is important to note that the effect sizes are small. This may be due in part to the outsized impact of COVID-19. Since arrests and bookings were already declining during this period, some of these findings may be explained by the impact of COVID-19 rather than the interventions.

Chapter 2
Crime Trends

This chapter answers research question 2 (How did crime overall change from the period before the SJC reforms to the post-implementation periods). Specifically, we examined whether bookings in general changed over the study periods, whether bookings for violent crimes changed, and whether changes in booking trends look different for Black, Indigenous, and People of Color (BIPOC) individuals compared to those for white individuals.

Analytic Approach

In each site, we tracked crime rates over the three time periods described in Chapter 1 (see Table 1.1), from pre-implementation of the SJC strategies through an early post-implementation 1 period and up to 24 months following a later post-implementation 2 period. Based on the assumption that the early post-implementation period is likely to see trends driven by local efforts to accelerate jail reduction efforts due to the COVID-19 pandemic, we include this period in part as a benchmark against which late post-implementation trends can be contextualized.

In New Orleans, we examined monthly booking counts from May 2015 to April 2023. PSA implementation began in 2018, with a post-COVID-19 implementation period beginning in 2022.[18] In Lucas County, we used a similar approach, looking at monthly bookings from June 2013 to April 2023. While SJC reforms kicked off in 2015, these analyses focus specifically on the use of the PSA, which was implemented beginning in 2016.

We used an interrupted time series approach to understand booking trends in New Orleans and Lucas County. Both the early and late post-implementation dates were used to test whether the trend following the date was significantly different from the trend prior to the date. Due to data limitations and the specifics of SJC implementation in the two sites, it is not possible to distinguish specifically which (if any) of the observed trends are specifically attributable to the implementation of the PSA as opposed to other SJC strategies implemented in the sites.

A comprehensive description of the methods employed is presented in Appendix B.

Results

New Orleans

Overall Crime Figure 2.1 shows data reported by the Federal Bureau of Investigation (FBI) available in the Uniform Crime Report (UCR), reflecting offenses known to the police. Property charges make up the majority of offenses. In New Orleans, property crimes rose slightly (18% increase) throughout the period from 2015 (mean of 1,299) through 2023 (mean of 1,544).

Violent offenses also rose slightly from an average of 325 offenses in 2015 to 413 offenses in 2023 (27% increase).

Figure 2.1. Offenses Known to Police (NOLA)
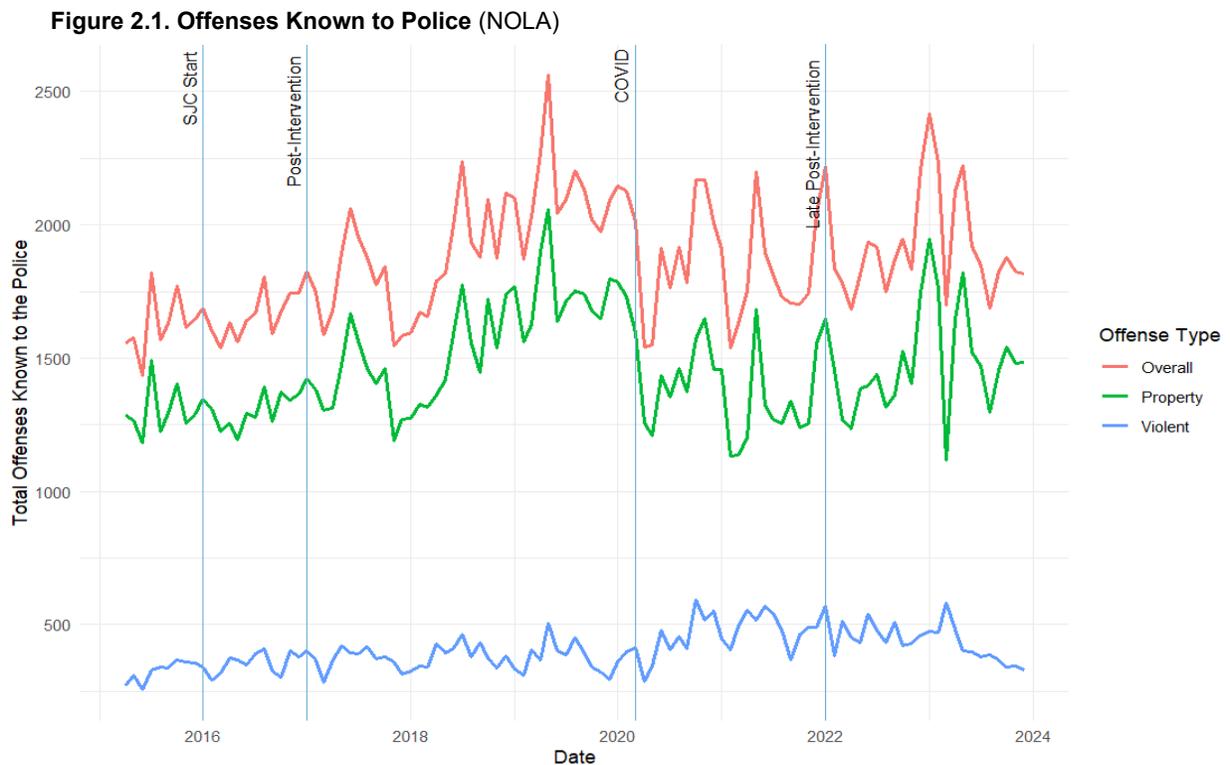
Violent vs. Nonviolent Crime Figure 2.2 shows the trend of monthly bookings overall and for violent and nonviolent offenses throughout the study period for New Orleans. Bookings in New Orleans declined steadily throughout the study period, with a large drop of 52% from 1,028 bookings in February 2020 to 492 in April 2020 (likely a result of COVID-19). Bookings for violent offenses remained steady throughout the study period. At the highest pre-COVID-19 point, there were 1,844 bookings in July 2017 while the highest post-COVID-19 total was 781— a 58% decrease. Following the drop in bookings during COVID-19, bookings overall and for nonviolent offenses have climbed slightly from the lowest point (492 in April 2020) to an average of 637 in 2022 and 2023 (29% increase).

Race Monthly booking trends by race are shown in Figure 2.3.[19] While about 33% of the overall population in New Orleans is white, white individuals account for only 11% of the jail population; 56% of the overall population is Black, but Black individuals make up 87% of the jail population.[20] Generally, monthly bookings decreased steadily throughout the study period followed by a precipitous drop during COVID-19. Following the pandemic and a brief stabilizing period, there has been a slight upward trend in bookings for BIPOC individuals. At the same time, there has been a slight downward trend in bookings for white individuals.

Figure 2.2. Time Series Plot of Monthly Bookings by Type of Offense (NOLA)
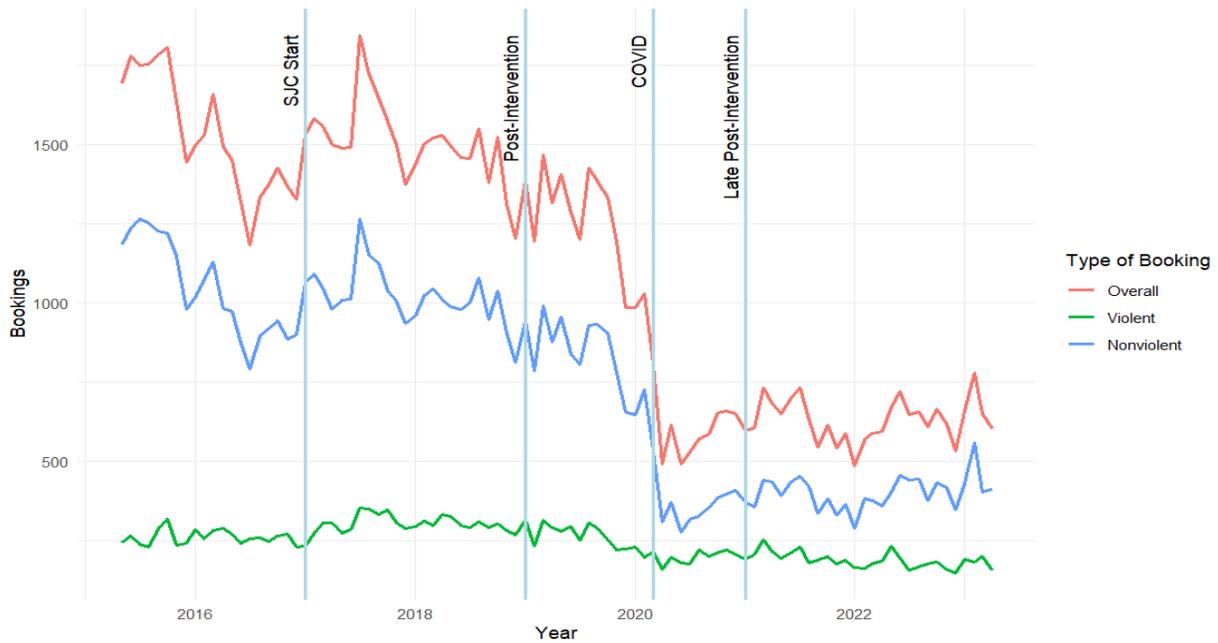
Figure 2.3. Time Series Plot of Monthly Bookings by Race (NOLA)
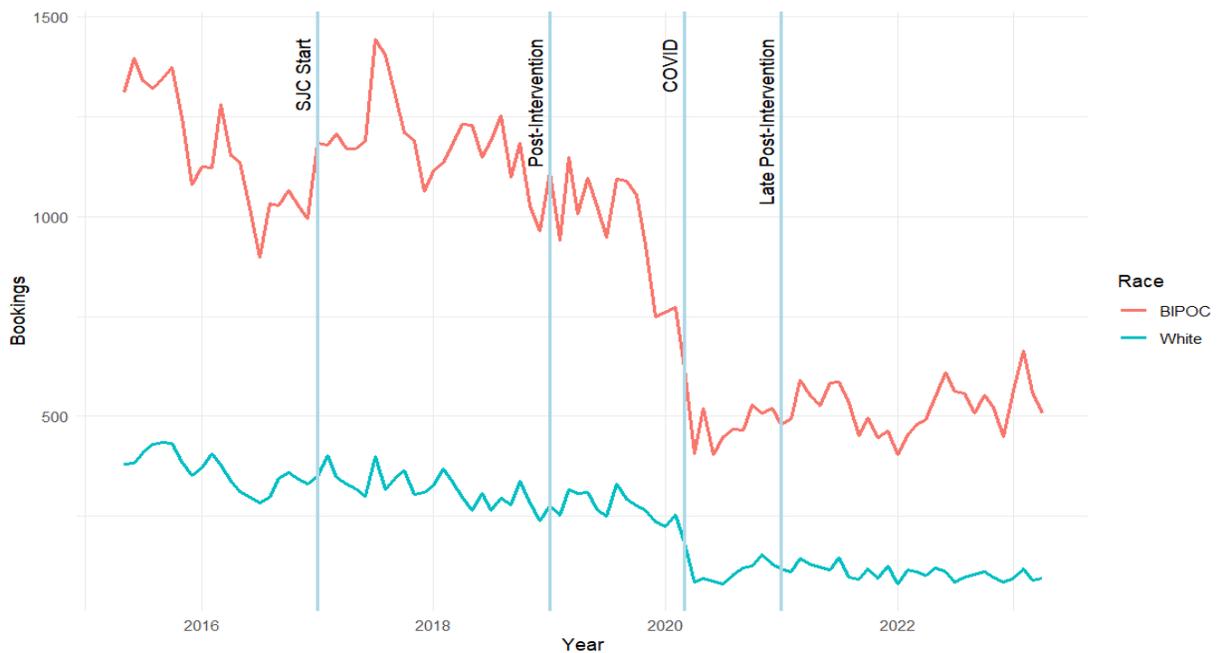
Forecast A 24-month forecast of overall bookings is shown in Figure 2.4. The solid line denotes actual monthly counts of bookings while the dashed line represents fitted values. Due to the large drop in monthly bookings during COVID-19, there is uncertainty in the model. However, the data show some evidence of stabilization where monthly bookings have only slowly increased following the COVID-19 period. At the upper predicted range, monthly bookings remain lower than pre-SJC reforms (1,484 predicted bookings vs. 1,844 bookings in

July 2017). To isolate the period prior to COVID-19 from the analyses, we examined an alternative model that tested the impact of SJC on booking trends. This alternative model did not show that SJC programming had a statistically significant impact on booking trends (b = 141.01, se = 198.51, p = 0.48). However, it is important to note that the period between the beginning of SJC programming and the beginning of COVID-19 mandates was comparatively short and may have impacted this finding.

Figure 2.4. 24-Month Forecast of Bookings (NOLA)
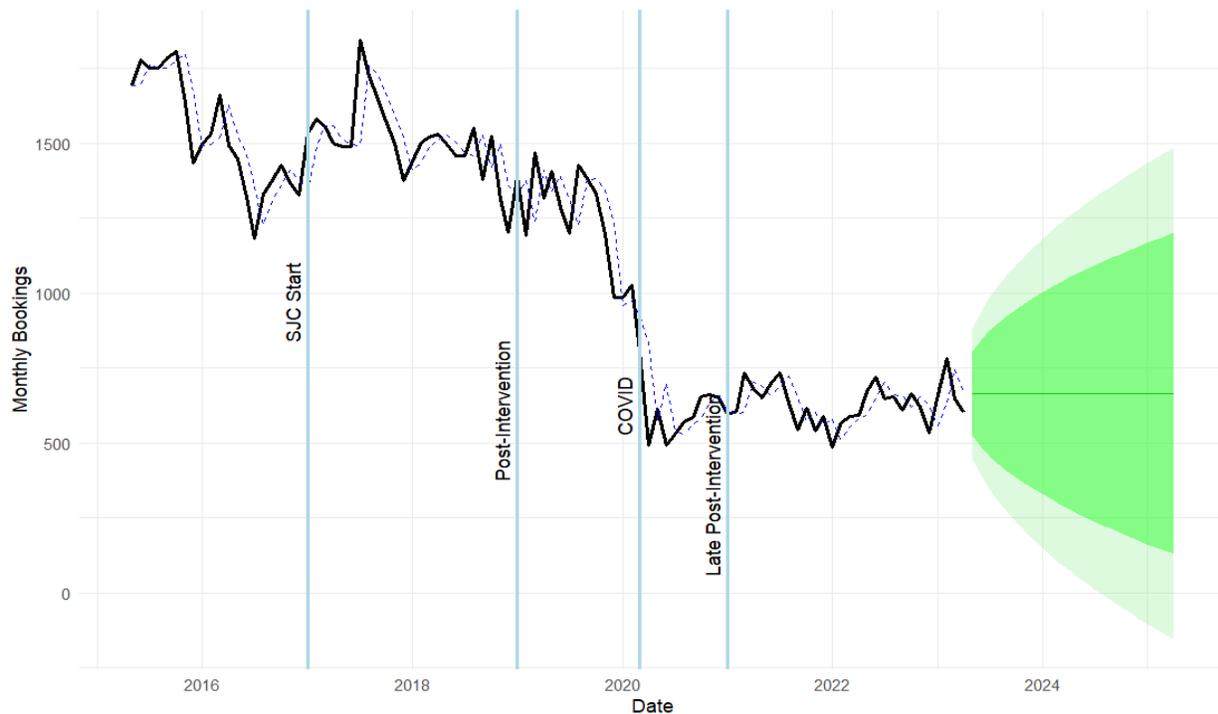
Note. Dotted line represents fitted values.

Lucas County

Overall Crime Figure 2.5 shows UCR data from April 2015 to December 2023. During this period, property crimes—which, as in New Orleans, make up the majority of offenses known to the police—have generally trended down (38% decrease) from a monthly average of 1,107 in 2015 to 677 in 2023. Violent offenses have stayed consistent across this time period, with a monthly average of 240 offenses in 2015 and 255 in 2023 (6% increase).

Violent vs. Nonviolent Crime Figure 2.6 shows the trends for monthly bookings overall, as well as breakouts for violent and nonviolent charges in Lucas County from June 2013 to April 2023. Generally, bookings declined steadily throughout the period prior to COVID-19. The number of monthly bookings dropped from 1,412 in February 2020 to 591 in April 2020, a 58% decrease. This precipitous drop immediately following the mid-March COVID-19 shutdown was followed by an incline from 591 bookings in April 2020 to 1,194 bookings in October 2020 (102% increase), although overall bookings remained lower at the end of the study period

compared to the period prior to COVID-19 (45% decrease from August 2013 to the highest post-COVID total in March 2023). While bookings for nonviolent offenses declined throughout the study period, bookings for violent offenses remained steady throughout.

Figure 2.5. Offenses Known to Police (Lucas County)
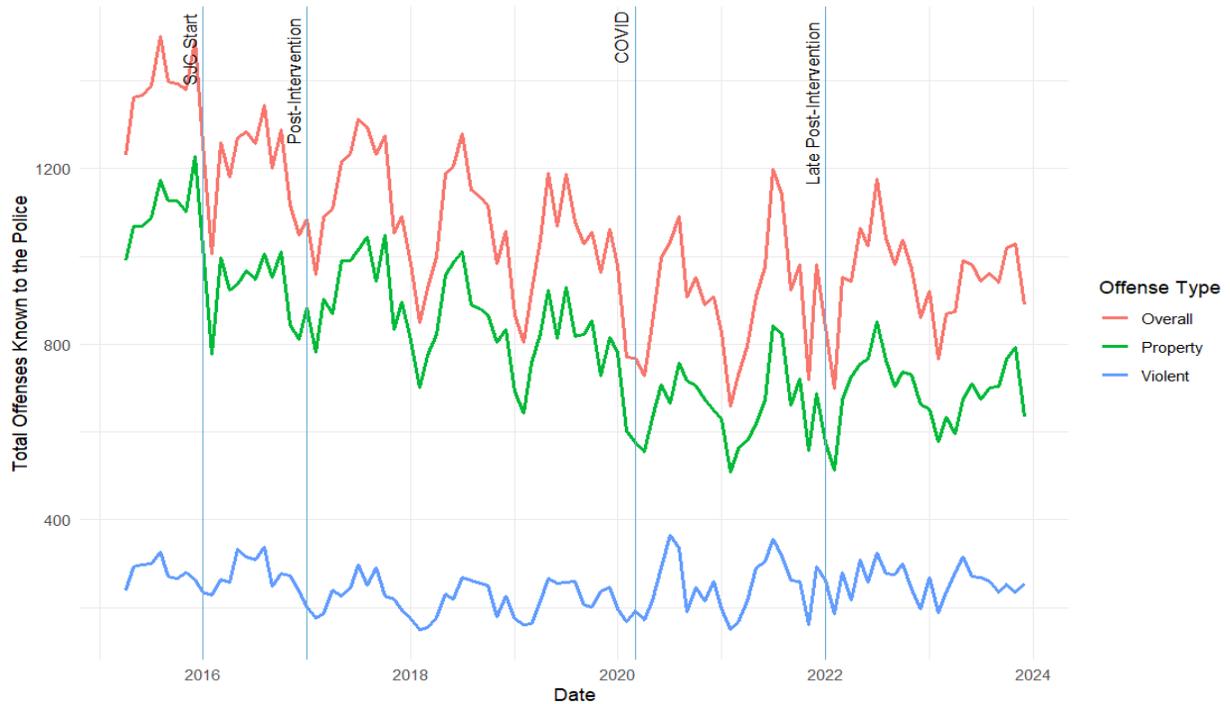
Figure 2.6. Time Series Plot of Monthly Bookings by Type of Offense (Lucas County)
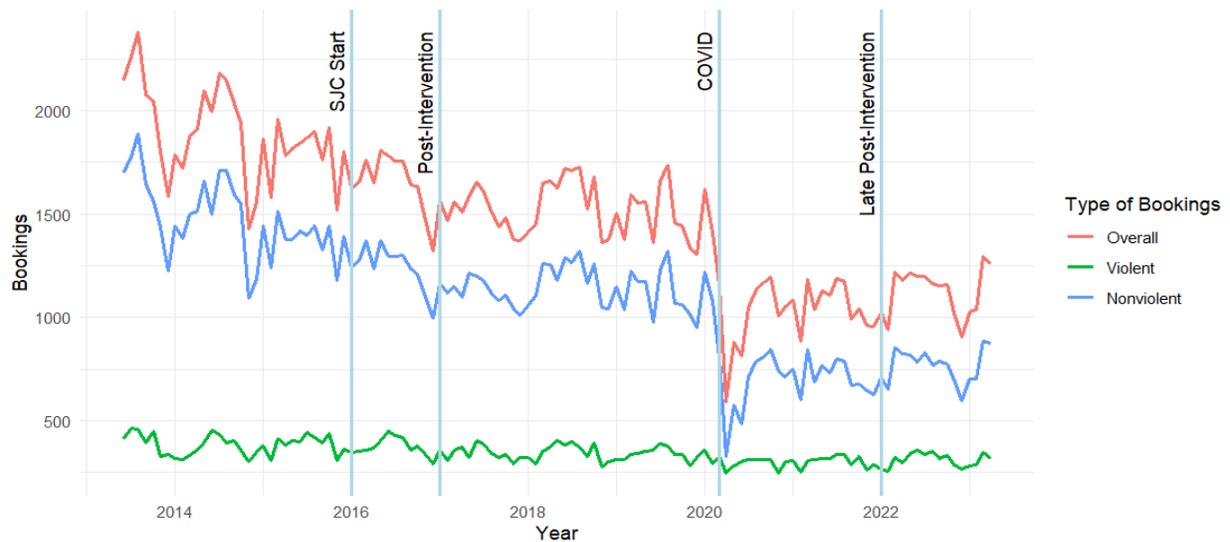
Race Figure 2.7 shows the trend of monthly bookings by race throughout the study period. The number of monthly bookings for both white and BIPOC individuals trended downward throughout the study period, though bookings for white individuals are consistently lower.[21] Of note is the overrepresentation of bookings involving BIPOC individuals throughout the study period. Bookings for BIPOC individuals outnumbered bookings for white individuals during

each of the months for which we had data. These data mirror the data reported by the Vera Institute, which indicate that white individuals made up 68% of the general population and 38% of the jail population in Lucas County, while Black individuals make up 21% of the overall population and 59% of the jail population.**Error! Bookmark not defined.**

Figure 2.7. Time Series Plot of Monthly Bookings by Race (Lucas County)
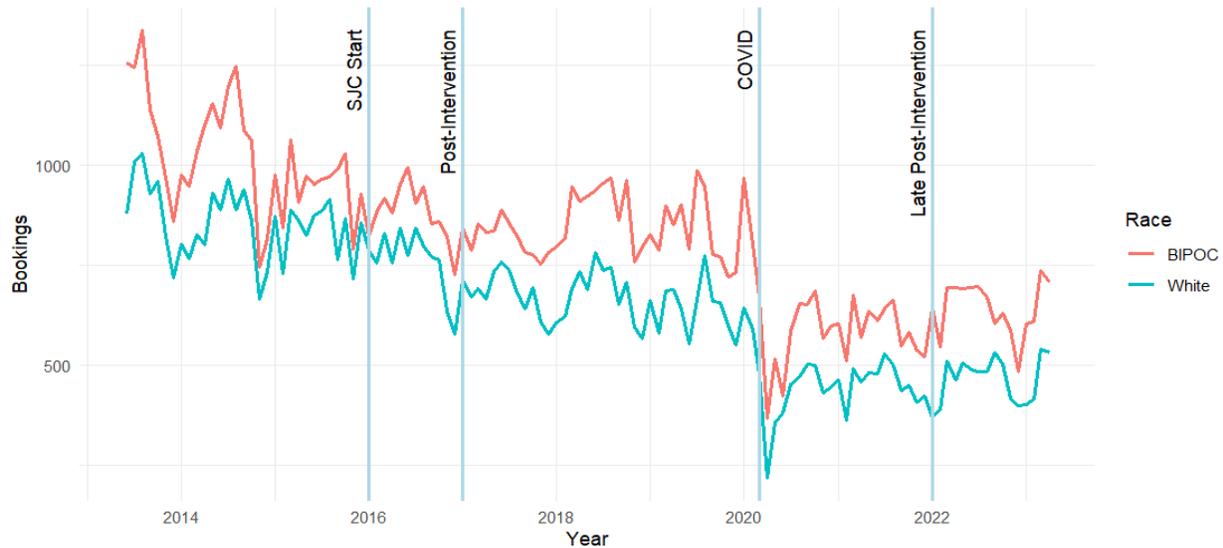
Forecast Figure 2.8 shows the overall bookings throughout the study period, with a 24-month forecast of bookings through April 2025. The solid line represents actual values, while the dashed line represents fitted values. The impact of COVID-19 on bookings in Lucas County was and continues to be sizeable. Due to the precipitous drop in March 2020, the range of the forecast (marked in light green indicating the upper and lower 80% confidence interval and grey indicating the upper 95% confidence interval in Figure 5.8) is broad. Overall, bookings dropped 63% from January to March 2020 as a direct result of COVID-19, which introduced a great deal of uncertainty in the model and increased the range of predictions. Fitted values were furthest from actual values immediately after COVID, particularly in July 2020 (1,049 actual bookings compared to 1,398 predicted) as bookings gradually increased. It is important to note that at the upper end of the prediction, monthly bookings are still lower than at the beginning of SJC reforms (1,700 bookings predicted at the upper bounds in March 2025 vs 2,381 actual bookings in 2013).

Generally, PSA implementation did not have a statistically significant impact on monthly booking trends. We hypothesized that the outsized impact of COVID-19 may mask the impact of PSA implementation. To test this hypothesis, we ran an alternative model that eliminated all data after December 2020. This model did show a small decline that was not statistically significant in monthly bookings following PSA implementation (b = -71.38, se = 63.57, p=0.26).

Figure 2.8. 24-Month Forecast of Bookings (Lucas County)
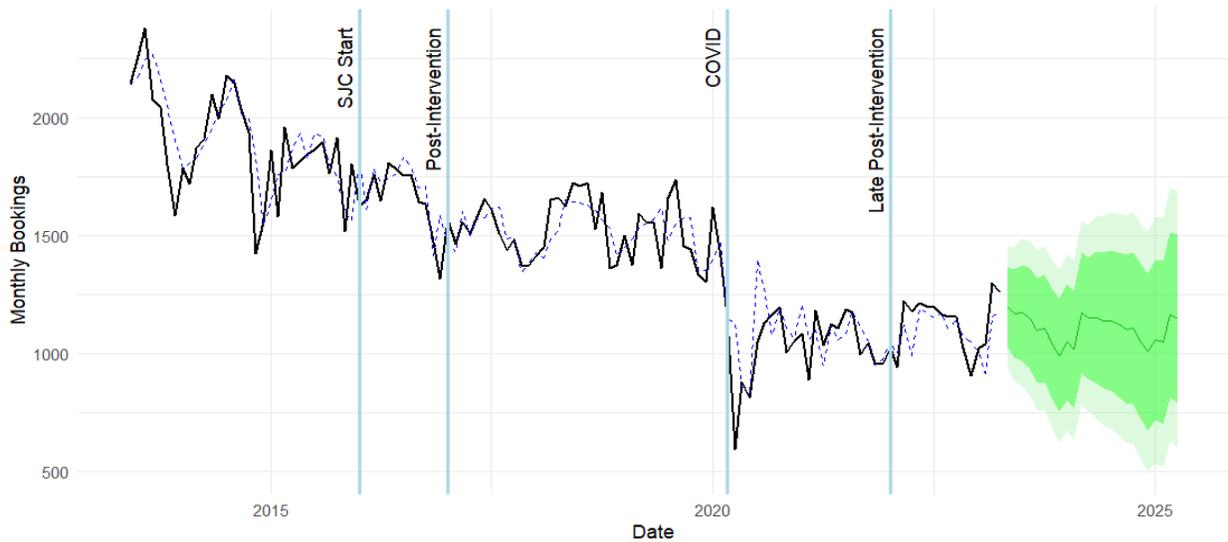
Key Takeaways, Crime Trends

Trends in monthly bookings show <u>a steady decline</u> throughout the study period. While evidence of the impact of PSA implementation in both sites was inconclusive, the data did show a small program effect, particularly when examining the pre-COVID-19 data in Lucas County. For both sites, COVID-19 introduced large variability in the trends that resulted in a less precise prediction. Data suggest that we are currently in a stabilization period, where booking trends remain lower than the pre-COVID-19 levels. It is also important to note that while the number of offenses known to police overall remained steady in New Orleans, the number of bookings declined dramatically during the study period.

There were <u>significant racial disparities</u> in monthly bookings. BIPOC individuals were consistently overrepresented in bookings across the study period in both sites. To understand the extent of racial disparity in the two sites, we calculated the Relative Rate Index (RRI) based on the median monthly bookings during the study period.[22] For both sites, bookings were twice as likely to involve BIPOC individuals than white individuals. While booking trends in both sites involving both white and BIPOC individuals showed a decline throughout the study period, we recommend monitoring data on racial disparity.

Chapter 3
Predictors of Recidivism

In this chapter, we seek to answer the following questions (research question 3): Did repeat returns to jail increase or decrease over time? Were there changes in recidivism from the period before the SJC reforms to the post-implementation period? Specifically, were there changes in new bookings on any charge, felony charges, or violent charges over this period? Did trends in recidivism differ based on personal or case characteristics (e.g., by demographics, criminal history)?

Analytic Approach

To understand the effect of SJC reforms on recidivism, we first defined recidivism as a binary outcome of a re-booking for either a felony or misdemeanor offense. We estimated logistic regression models predicting both one-and two-year recidivism from gender, race, SJC cohort (pre-implementation, post-implementation 1, post-implementation 2), prior misdemeanor, prior felony, relative neighborhood deprivation,[23] and the number of days in jail on the initial case. Additionally, we examined logistic regression models predicting one- and two-year recidivism specifically for a violent offense. We did not have a full two years of data for the post-implementation 2 group in either New Orleans or Lucas County, therefore all two-year recidivism models include only the pre-implementation and post- implementation 1 groups. (Figures presenting two-year recidivism rates are presented in Appendix C.)

In addition to predicting recidivism, we examined the impact of SJC strategies on days spent in jail for initial bookings in the two study sites. We used ordinal logistic regression to predict days in jail from gender, race, SJC cohort, prior misdemeanor, prior felony, and relative neighborhood deprivation.[23] The analyses presented below are intended to answer whether SJC reforms had a measurable impact on recidivism as defined as a binary outcome.

Results

New Orleans

Felony Recidivism Each figure in this section presents the predicted probability of recidivism and days in jail for each SJC cohort. Figure 3.1 shows the predicted probability of felony

> **Relative Neighborhood Deprivation**
>
> A zip code level measure created using the U.S. Census' 2022 American Community Survey. Neighborhood indicators of income, education, employment, and housing quality were used to create a composite score, with higher scores indicating higher levels of neighborhood level deprivation.

recidivism in the first year after the initial booking. The pre-implementation cohort had a predicted probability of felony recidivism of 22.6%. The post-implementation 1 group had the highest predicted probability of 28.1%, while the post-implementation 2 group had the lowest probability of recidivism (6.3%). Tables showing the model with all covariates are included in Appendix D.

At 2 years, the predicted probability of felony recidivism for the pre-implementation group was 33.0% compared to 38.4% for the post-implementation 1 group (see Appendix C).

Figure 3.1. Predicted Probability of Recidivism at 1 Year (NOLA)
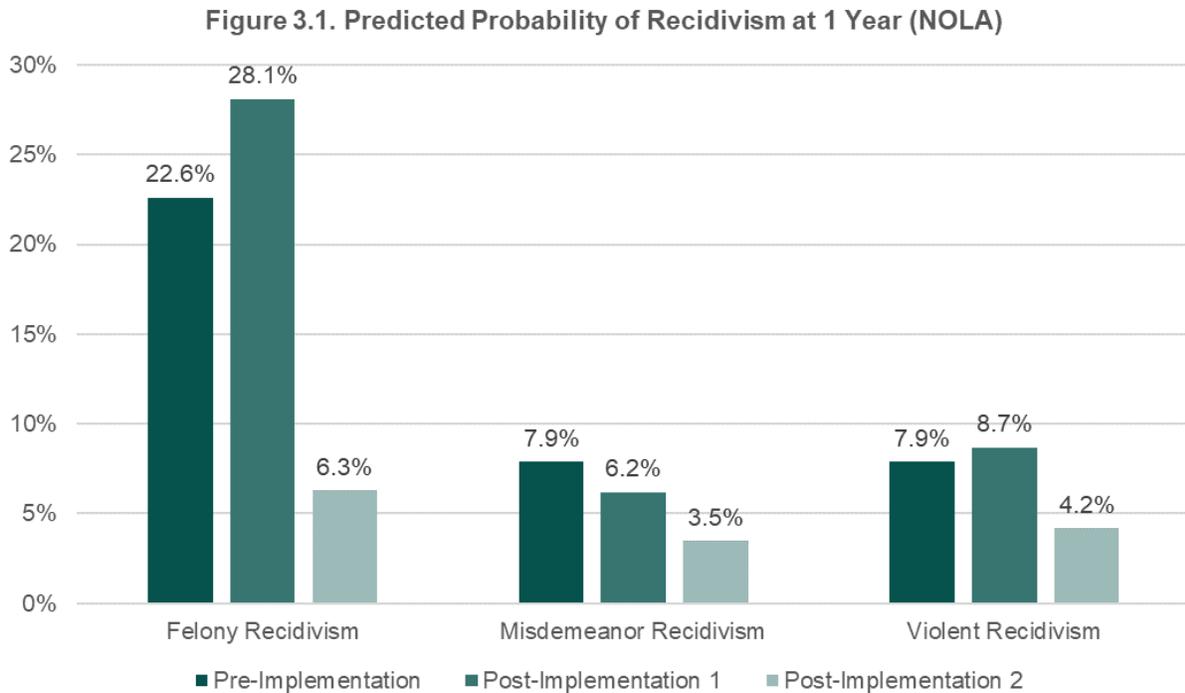
Misdemeanor Recidivism In addition to felony recidivism, we estimated the probability of misdemeanor recidivism as defined as a rebooking for a misdemeanor offense. The predicted probability for the pre-implementation cohort was 7.9%. Both the post- implementation 1 and 2 cohorts had lower probabilities of misdemeanor recidivism (6.2% and 3.5% respectively; Figure 3.1). At 2 years, the pre-implementation cohort had a 11.4% probability of misdemeanor recidivism while the post- implementation 1 group had a slightly lower probability (10.5%; see Appendix C).

Violent Recidivism We defined violent recidivism as a subsequent booking for any violent offense.[24] Figure 3.1 show the predicted probability of violent recidivism for the SJC cohorts. Similar to the data on felony recidivism, the post-implementation groups had a higher probability of violent recidivism compared to the pre-implementation group. At one year after the initial booking, the post-implementation 2 group had the lowest probability of violent recidivism (4.2%).

Time in Jail on the Initial Case Figure 3.2 presents predicted probabilities from an ordinal logistic regression model estimating the number of days in jail on the initial case. For each cohort (pre-implementation, post-implementation 1, and post-implementation 2), the most common amount of time spent in jail on the initial booking was less than one week (59.1% pre-implementation, 58.3% post-implementation 1, 54.3% post-implementation 2). The probability of receiving no jail time was highest in the post-implementation 2 cohort (35.1%, compared to 24.3% pre-implementation and 26.9% post-implementation 1). Longer stays in jail were relatively uncommon for each cohort, but were slightly more common in the pre-implementation cohort. Additionally, the pre-implementation cohort had a higher probability of experiencing jail stays longer than a week.

Figure 3.2. Predicted Jail Time on the Initial Case (NOLA)
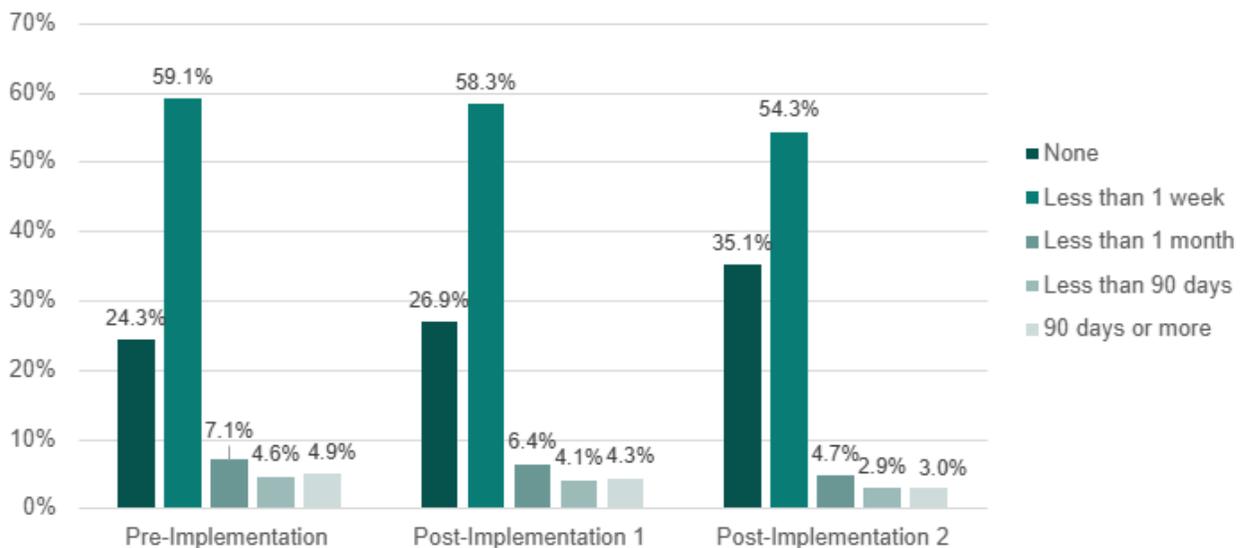
Covariates The full models presented in Appendix D additionally include covariates hypothesized to be drivers of recidivism. Findings in New Orleans include:

- **White individuals had significantly lower odds of recidivism than BIPOC individuals** for new misdemeanors, felonies, and violent offenses (e.g., see felony probabilities for both sites in Figure 3.5).
- **Men had significantly higher odds of felony recidivism than women.** This was also true for new violent offenses (at 2 years only).
- **Those with prior bookings also had higher odds of a new booking** on misdemeanor, felony, and violent offenses.
- However, **a history of prior felonies did not increase the odds of violent recidivism** (2 years).
- **Relative neighborhood deprivation[23] measures did not predict violent recidivism.**

- **Those who spent more than a week in jail on the initial booking had greater odds of felony recidivism** on misdemeanor and felony charges.
- **Being male, BIPOC, and having a prior felony were associated with longer jail stays** on the initial booking.

Lucas County

Felony Recidivism In Lucas County, the data on recidivism shows that the post-implementation 2 cohort consistently had a lower probability of recidivism compared to the pre-implementation and post-implementation 1 cohorts. Figure 3.3 shows one-year felony recidivism for Lucas County SJC cohorts (two-year recidivism results are illustrated in Appendix C). Pre-implementation and post-implementation 1 cohorts had nearly equal probabilities of felony recidivism at both time points. The post-implementation 2 group had a significantly lower probability of recidivism at one year after the initial booking compared to the pre-implementation cohort (17.5% and 12.8%).

Figure 3.3. Predicted Probability of Recidivism at 1 Year (Lucas Co.)
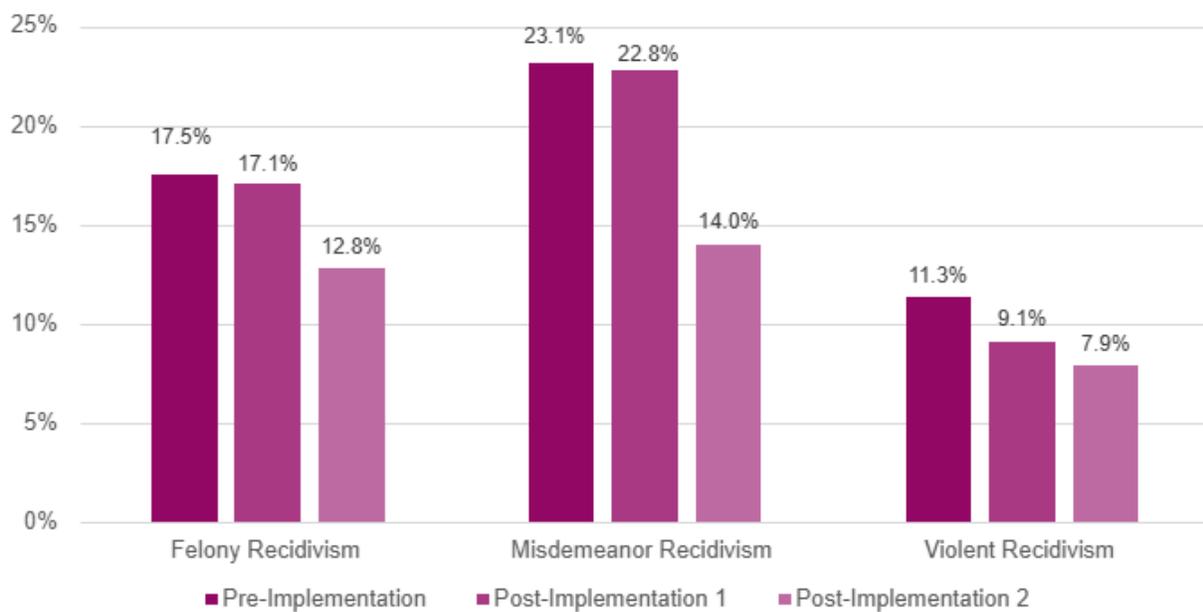
Misdemeanor Recidivism Similar to the felony recidivism findings, the probability of misdemeanor recidivism was nearly identical for the pre-implementation and post-implementation 1 groups, with the post-implementation 2 group having a significantly lower probability of misdemeanor recidivism (see Figure 3.3).

Violent Recidivism Predicted probability of violent recidivism is also shown in Figure 3.3. In contrast to the misdemeanor and felony outcomes, violent recidivism had clear separations between pre-implementation, post-implementation 1, and post-implementation 2 groups. At one

year, the pre-implementation group had an 11.3% probability of violent recidivism while the probability was 9.1% for the post-implementation 1 and 7.9% for the post-implementation 2 groups. At 2 years, the post-implementation 1 group had a significantly lower probability of violent recidivism (see Appendix C).

Time in Jail on the Initial Case Figure 3.4 shows the predicted probabilities of the number of days in jail on the initial case. Based on the distribution of jail days in Lucas County, the number of days in jail was split into three categories: no days, less than 1 week, and more than 1 week. For each cohort, the most common predicted outcome was less than 1 week in jail. The pre-implementation cohort had the lowest probability of having no time in jail and the highest probability of having more than 1 week in jail. The post-implementation 1 and 2 groups looked similar in the probability of spending no time in jail (31% for both) and having a jail stay of more than 1 week (18% for both).

Figure 3.4. Predicted Jail Time on the Initial Case (Lucas Co.)
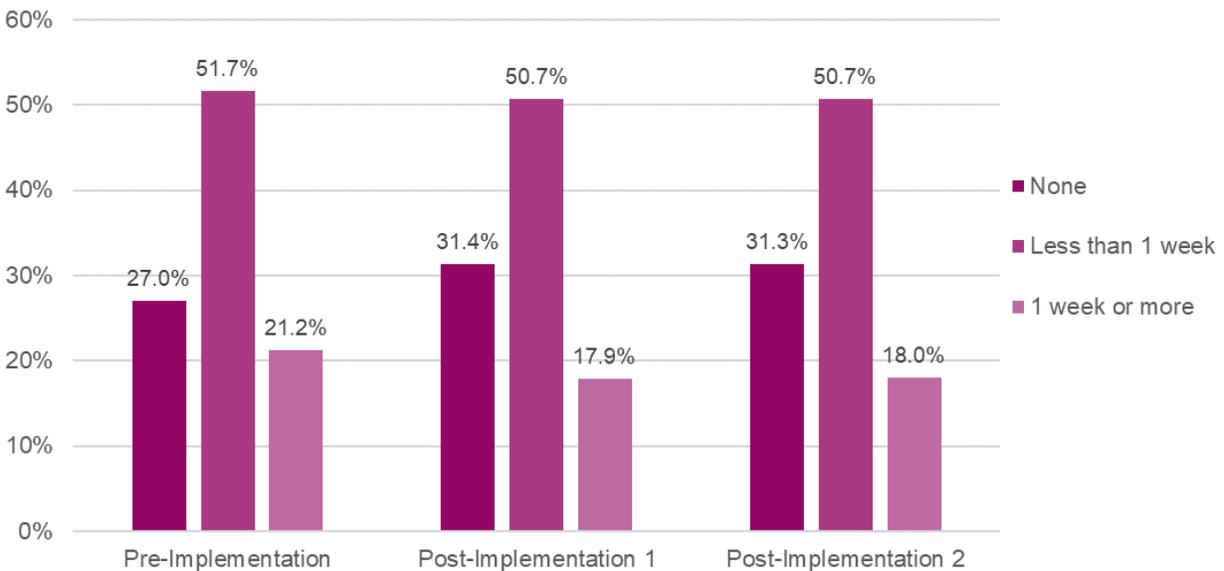
Covariates The full models presented in Appendix D additionally include covariates hypothesized to be drivers of recidivism. Findings in Lucas County include:

- **White individuals had significantly lower odds of recidivism than BIPOC individuals** for new misdemeanors, felonies, and violent offenses (e.g., see felony probabilities for both sites in Figure 3.5).
- **Men had significantly higher odds of recidivism than women.** This was true for new misdemeanors (at one year only), felonies, and new violent offenses.

- **Those with prior felony bookings were more likely to have a new felony offense.** Those with a prior felony booking had more than three times the odds of being booked for a new felony offense.

Figure 3.5. Predicted Probability of Felony Recidivism at 1 Year, by Race and Site
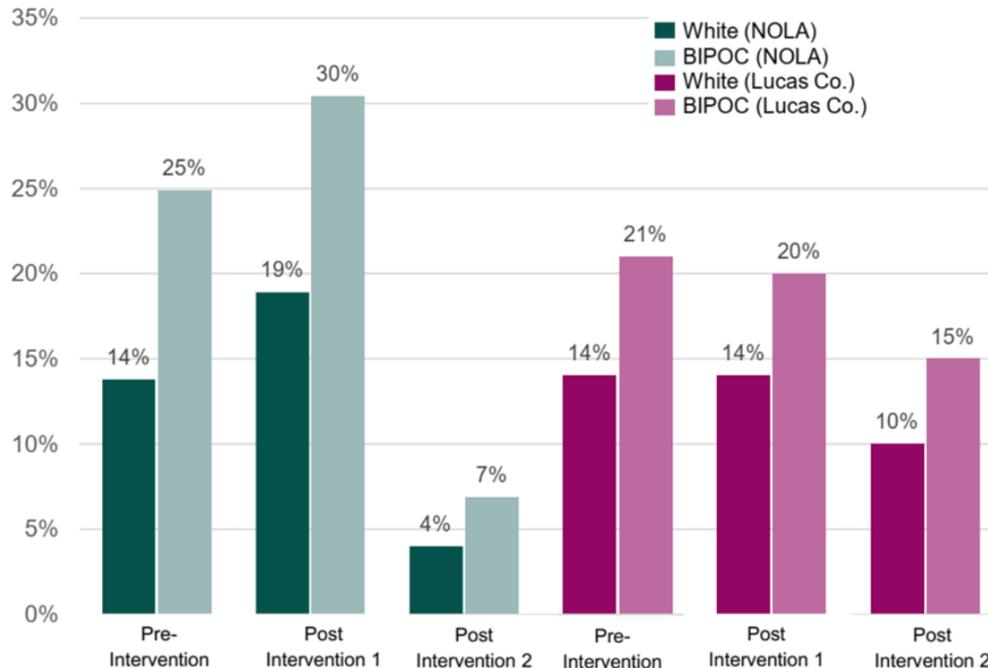
- **Those with prior misdemeanor bookings were more likely to have a new misdemeanor offense.** Those with prior misdemeanor bookings had nearly three times the odds of being booked for a new misdemeanor offense.
- **Relative neighborhood deprivation[23] was associated with a higher probability of violent recidivism.**
- **Being male, white, having a prior misdemeanor or felony, and relative deprivation were associated with longer jail stays** on the initial booking.

Key Takeaways, Predictors of Recidivism

Overall, recidivism decreased following SJC implementation. In New Orleans, an initial increase in recidivism during the post-implementation 1 period was followed by declining felony and violent recidivism during the post-implementation 2 period (misdemeanor recidivism was lower for each subsequent cohort). In Lucas County, the initial post-implementation 1 period saw stable recidivism rates, but felony and misdemeanor recidivism declined during the post-implementation 2 period (violent recidivism was lower for each subsequent cohort).

The results suggest that the types of jail-reduction strategies implemented through SJC in these sites did not come at the cost of community safety. We cannot with certainty attribute the observed declines in recidivism to SJC implementation—particularly in the context of the COVID-19 pandemic and resultant lockdowns, which have generally been linked to declining arrests and jail bookings.[25] We did make an attempt to distance the post-implementation 2 timeframe from the COVID-19 lockdowns by selecting samples from *after* 2020 (see Table 1.1), but arrests and bookings in the sites may have continued to be impacted by the pandemic (and other unmeasured circumstances).

Those with prior bookings had greater odds of future bookings. Given the sites' implementation of the PSA, which includes prior criminal history (convictions) as a risk factor, it is perhaps unsurprising that those with a recent criminal history (booking) are more likely to be booked on future run-ins with law enforcement. It is also worth noting that recidivism is not solely a measure of *behavior*, but a measure of who is more likely to be arrested and booked. However, it is worth noting that those with a history of felony bookings in the past two years did *not* have greater odds of a new violent incident.

In both sites, the proportion of those spending *zero* days in jail on the initial case increased over the life of the SJC strategies. In terms of the amount of time spent in jail on the initial case, the (small) majority of all samples spent some time—but less than one week—in jail. We observed increases in those bypassing jail altogether from the pre-implementation period to the post-implementation 1 period, and again from post-implementation 1 to post-implementation 2. While this project was not specifically seeking to confirm that SJC reduced jail time, these findings do support previous research finding that SJC has successfully reduced the use of jail.

Finally, it is worth noting that **those who spent more time in jail on the initial booking were more likely to have a recidivism incident**. Many of the covariates examined here—gender, race, criminal history—are static factors. The amount of time booked individuals spend in jail is one of the few alterable factors we examined. While there are likely other considerations at play, it is worth considering that by reducing the time spent in jail, it may be possible to reduce the likelihood of recidivism. This aligns with past research findings that longer jail stays increase criminogenic risk, in particular increasing recidivism among those who are otherwise at low risk for new criminal charges.[26]

Chapter 4
Survival Analysis

This chapter examines the criminal trajectory of individuals in the three time periods. Specifically, we answer the following components of research question 4: Regardless of changes in rates of recidivism, were there changes in the criminal trajectory among those with a new booking incident? Did the amount of time to a new booking differ?

Analytic Plan

To understand the impact of SJC strategies on time to recidivism, we examined the impact of strategies implemented in the study sites by examining the time to rebooking within one- and two-year windows.[27] Recidivism here is defined as a new booking for any type of offense at 365 and 730 days. Cases were right censored at those times to indicate that for some cases, there was no recidivism event. We estimated a Cox proportional hazards model estimating time to recidivism controlling for gender, race, prior misdemeanor/felony,[28] relative deprivation,[23] and time in jail for the initial charge.[29] Hazard Ratios (HR) greater than 1 indicate a likelihood of recidivism sooner. For example, a hazard ratio for males of 1.67 indicates that the rate of recidivism is 67% higher for males than females on any given day within the study period, controlling for other variables in the model. Previous criminal history was defined as a misdemeanor offense or a felony offense up to two years preceding the initial charge.[30]

Results

New Orleans

Figure 4.1 shows a survival curve plotting the probability of not recidivating over 365 days by cohort (pre-implementation, post-implementation 1, and post-implementation 2). The Log-rank test showed statistically significant differences across groups ($\chi^2(2) = 118$, p <.001). Survival curves diverged early, particularly for the post-implementation 2 group. The pre-implementation and post-implementation 1 groups had similar rates of survival throughout the study period. Pre-implementation and post-implementation 1 groups recidivated more than expected (280 recidivism events vs. 224; 252 vs. 184) while the post-implementation 2 group recidivated far less than the expected rate (74 vs. 198). While there was no statistically significant difference in the pre-implementation and post-implementation 1 groups, the post-implementation 2 group had a substantially lower hazard of recidivism compared to the pre-implementation group. The post-implementation 2 group had a 68% lower instantaneous rate of recidivism. An instantaneous recidivism rate is the daily probability of recidivism occurring for each group among those who are still at risk for recidivism, i.e., those who have not yet recidivated. In other words, on any

given day during the study period, the post-implementation 2 group had a 68% lower rate of recidivism than the pre-implementation group.

Figure 4.1. One-Year Survival Analysis (NOLA)

	At Risk							
cohort_label=baseline	929	873	822	776	744	710	683	658
cohort_label=intervention	773	726	687	642	602	565	543	527
cohort_label=post intervention	737	718	700	697	685	678	668	664
	Events							
cohort_label=baseline	0	56	107	154	185	219	247	271
cohort_label=intervention	0	48	87	131	172	209	231	246
cohort_label=post intervention	0	19	38	40	52	59	69	73
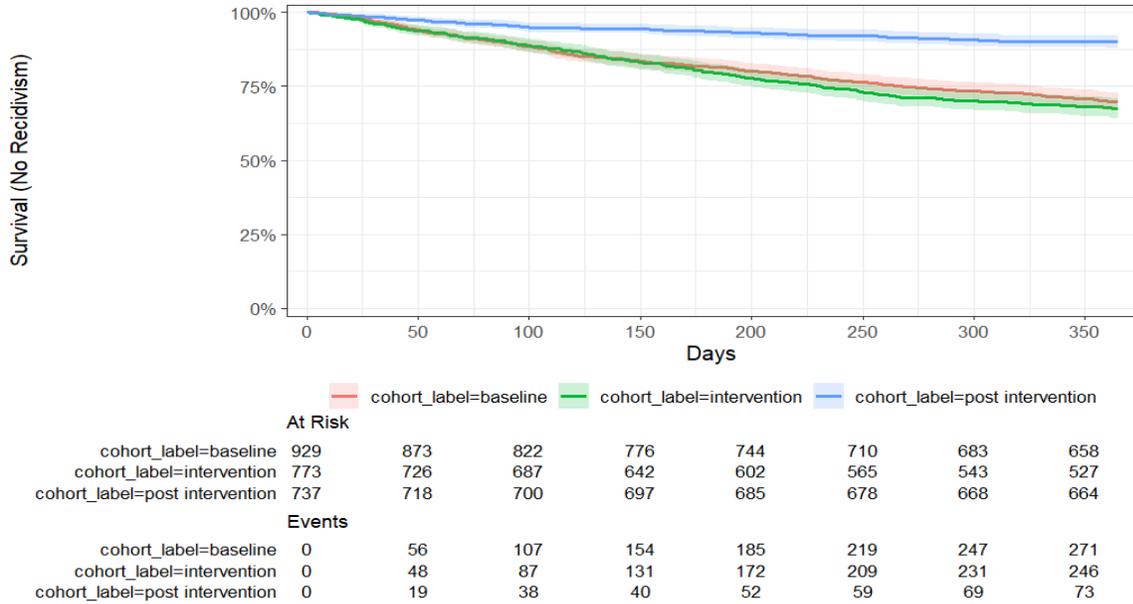
Note. $\chi^2(2) = 118$, $p < .001$; Numbers at risk and cumulative recidivism events are displayed at regular intervals beneath the plot. Shaded areas represent 95% confidence intervals.

Figure 4.2. Two-Year Survival Analysis (NOLA)

cohort_label=baseline								
At Risk	983	876	791	726	675	639	620	594
Events	0	107	192	258	308	344	363	389
cohort_label=intervention								
At Risk	810	724	636	572	542	516	488	463
Events	0	87	175	239	268	294	322	347
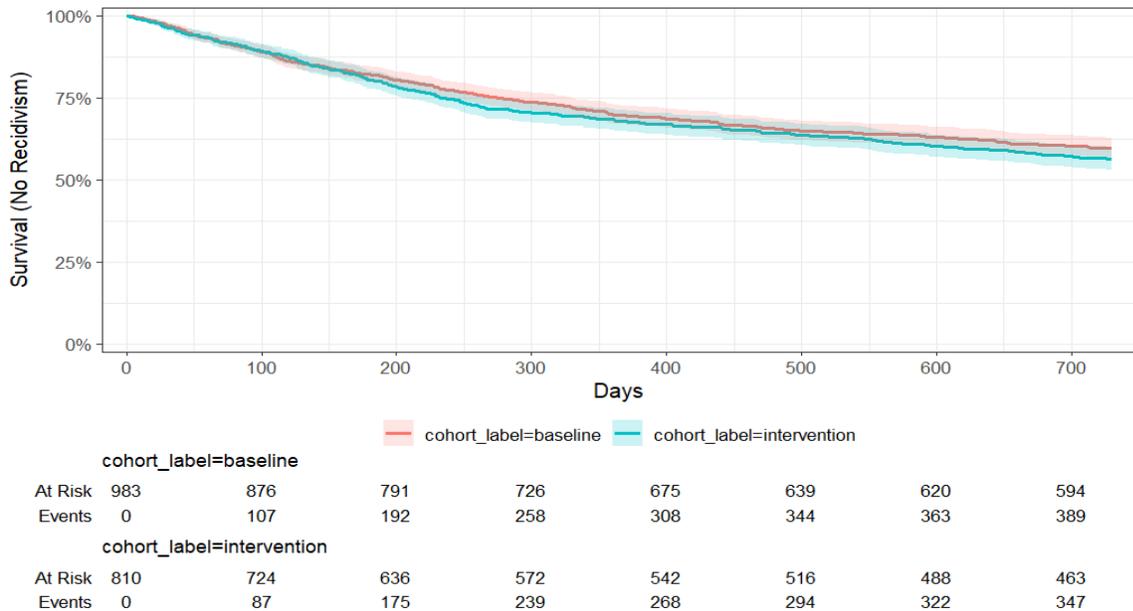
Note. $\chi^2(1) = 1.7$, $p = 0.2$; Numbers at risk and cumulative recidivism events are displayed at regular intervals beneath the plot. Shaded areas represent 95% confidence intervals.

Figure 4.2 shows a similar survival curve plotting the probability of survival over 730 days for the pre-implementation and post-implementation 1 cohorts. (There was not sufficient follow-up time to complete the two-year analysis for the post-implementation 2 group.) The Log-rank showed no statistically significant difference between the pre-implementation and post-implementation 1 groups. The pre-implementation group recidivated slightly less than the expected value (397 vs. 415) while the post-implementation 1 group recidivated slightly more (353 vs. 335).

At both 365 and 730 days, the Cox proportional hazards models (Appendix E) show that gender, race, and prior criminal history were significant predictors of time to recidivism. Criminal history was a particularly strong predictor. At 365 days, individuals with a prior misdemeanor booking had a 78% higher instantaneous recidivism rate, and individuals with a prior felony had an 84% higher rate of recidivism.

Lucas County

For Lucas County, one-year follow up data showed significant group differences (see Figure 4.3). Survival curves for the three groups diverged early and remained separated throughout the study period. The Log-rank test was statistically significant, indicating that the survival curves were substantively different for the three groups ($\chi^2(2) = 17.4$, $p < .001$). The pre-implementation group had significantly more recidivism events than expected (415 recidivism events vs. 359) while the post-implementation 1 group had slightly more (378 vs. 376) and post-implementation 2 group had significant fewer (323 vs. 381). The Cox proportional hazards model did not show any significant group differences for the post-implementation 1 group compared to the pre-implementation. However, the post-implementation 2 group had a 15% lower instantaneous recidivism rate. On any given day in the study period, the post-implementation 2 group had 15% lower rate of recidivism.

Two-year survival curves for the pre-implementation and post-implementation 1 groups in Lucas County are shown in Figure 4.4. The Log-rank was not statistically significant, suggesting that there was no difference between the pre-implementation and post-implementation 1 groups ($\chi^2(1) = 2$, $p = 0.2$). The pre-implementation group had more observed recidivism events than the expected value (525 vs. 502) and the post-implementation 1 group had fewer observed recidivism events (503 vs. 526). Neither of these comparisons between the observed and expected values were statistically significant.

Cox proportional hazards models showed strong associations between previous criminal history and the instantaneous recidivism rate. On any given day within the study period, an individual with a history of a misdemeanor offenses had a 152% higher instantaneous recidivism rate while an individual with history of a felony offenses had a 100% higher rate.

Figure 4.3. One-Year Survival Analysis (Lucas County)

At Risk								
group=Baseline	930	773	699	642	599	572	543	523
group=Intervention	936	810	737	678	640	616	588	565
group=Late Intervention	932	794	738	690	662	641	624	611
Events								
group=Baseline	0	158	232	288	331	360	387	409
group=Intervention	0	128	201	260	297	321	349	373
group=Late Intervention	0	138	194	242	270	291	308	321
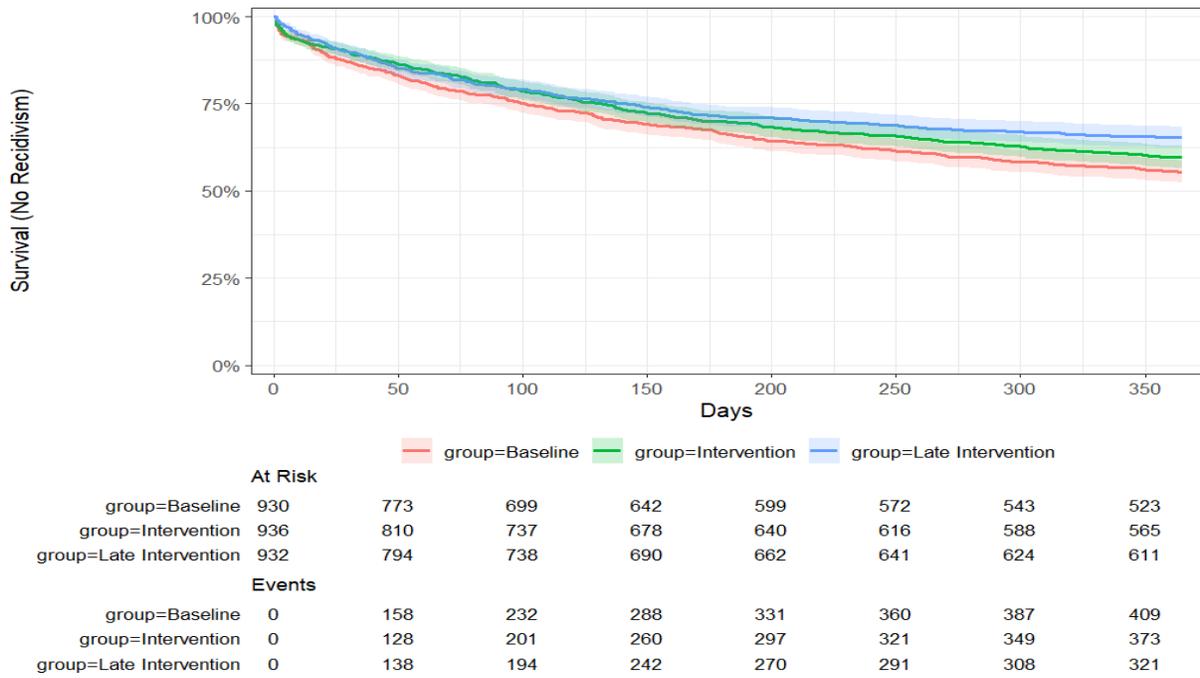
Note. $\chi^2(2) = 17.4$, $p < .001$; Numbers at risk and cumulative recidivism events are displayed at regular intervals beneath the plot. Shaded areas represented 95% confidence intervals.

Figure 4.4. Two-Year Survival Analysis (Lucas County)

group=Baseline								
At Risk	980	737	630	572	526	496	478	459
Events	0	244	350	408	454	485	502	521
group=Intervention								
At Risk	977	772	672	619	569	538	504	482
Events	0	207	306	359	408	439	473	495
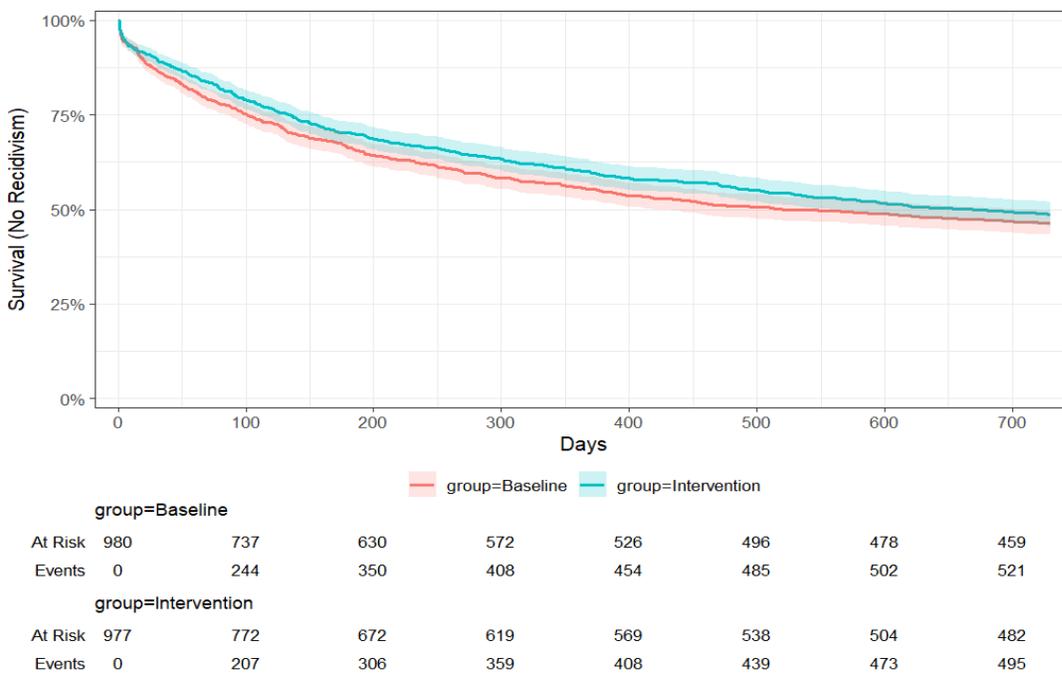
Note. $\chi^2(1) = 2$, $p = 0.2$; Numbers at risk and cumulative recidivism events are displayed at regular intervals beneath the plot. Shaded areas represented 95% confidence intervals.

Key Takeaways, Survival Analysis

In both sites, **individuals in the post-implementation 2 group recidivated less than expected**. These individuals had significantly less risk of recidivism at one year than individuals in the pre-implementation period—that is, there *were* changes in criminal trajectories at the later follow-up period of the SJC strategies. Again, these findings suggest that the SJC jail reduction strategies were implemented without sacrificing community safety.

Criminal history was predictive of time to recidivism in both sites. **Individuals with a history of either misdemeanor or felony bookings had higher recidivism rates**.

Chapter 5
Latent Class Analysis

This chapter further examines the criminal trajectory of individuals in the three time periods. Specifically, we answer the following components of research question 4: Regardless of changes in rates of recidivism, were there changes in the criminal trajectory among those with a new booking incident? Were there identifiable subgroups of individuals based on type and severity of charges and, if so, are there differences in recidivism for these groups?

Analytic Plan

Using the same sample as the logistic regression and survival analysis models, we examined whether there were identifiable groups based on their booking patterns. Using Latent Class Analysis, we identified groups of individuals based on the initial booking charge and any charges they were booked for in the one year prior for everyone in the three cohorts. We first identified the types of offenses that had adequate incidence rates for the two sites. For New Orleans, we selected seven charges: violent offenses, public nuisance/traffic,[31] driving under the influence (DUI), theft, burglary, drug offenses, and weapons offenses. In Lucas County, there were eight charge categories that had a sufficient incidence rate to include as classes: violent offenses, public nuisance, DUI, traffic offenses, theft, domestic violence, drug offenses, and weapons offenses.

To categorize individuals based on offending patterns, we conducted a latent class analysis (LCA) using Mplus version 8.10.[32] Latent class analysis is a statistical technique used to identify subpopulations in observed categorical data based on shared characteristics. In this case, LCA was used to identify groups of individuals based on the types of offenses in their instant case and in their one-year case history.

To determine the solution that best fits the data, we tested six models. We examined the relative fit of each of these models by considering several indicators generally used in the literature, including the Akaike Information Criterion (AIC), the sample size adjusted Bayesian Information Criterion (aBIC), Entropy, average latent class posterior probability, and the Lo-Mendell-Ruben test (LMRT).[33] The AIC and aBIC are log likelihood measures where lower values indicate greater comparative fit.[34] Entropy is a measure of the model's ability to define classes accurately, with values approaching one indicating a clear class separation.[35] While there is no absolute cut-off value, entropy values greater than .8 generally indicate an acceptable fit.[36] The average latent class posterior probability indicates the average probability that an individual is correctly classified by the model. Values approaching one indicate that the model can correctly assign individuals to subgroups with a low likelihood of misclassification. Finally, we examined the

LMRT as an indicator of whether the model being tested is superior to a model with one fewer class with significant p-values indicating a better fit.[37] Once we identified the best-fitting model, we examined the probability of item endorsement, in this case the probability of having been booked for a specific type of offense, across latent classes to describe the meaningful differences between the subgroups. Then, we examined whether gender, race, cohort, and relative deprivation predicted class membership using a 3-step multinomial regression approach. Where possible, we examined whether class membership predicted one-year recidivism using a distal outcomes approach.[38]

Results

New Orleans

Model Fit and Selection Table 5.1 shows model fit indices for LCA models testing k number of classes. For each of the models tested, AIC and aBIC decreased compared to the k-1 class solution, indicating a better fit to the data. Additionally, significant LMR values indicated that each of the models improved upon the k-1 solution. We found good entropy values for each of the solutions indicating high levels of classification accuracy.

While several models showed good fit, the 4-class model was chosen as the best fitting model. The 6-class solution included at least 3 classes with low group membership and was rejected. The 5-class solution included a redundant class where two groups were not substantively different. Therefore, we retained the 4-class solution as the best fitting model. Compared to the 3-class solution, the 4-class solution showed reductions in both the AIC and aBIC, a good entropy value, and a statistically significant LMR test. The 4-class solution also had good average posterior probabilities >.7 indicating good classification certainty and well-separated classes.

Table 5.1. Four Class Model was Retained as Best Fitting Solution

Number of Classes	AIC	aBIC	Entropy	LMR
1	13245.34	13264.16		
2	12357.88	12398.18	0.996	889.28***
3	12058.91	12120.69	0.985	310.05***
4	11931.27	12014.55	0.92	141.38***
5	11786.12	11890.88	0.94	158.64***
6	11754.58	11880.84	0.94	46.79***

Figure 5.1 shows the probability of having been charged with the seven different types of offenses in the model. The 4-class model included a group with a history of primarily (1) drug offenses, (2) theft and nonviolent offenses, (3) multiple types of offenses, and (4) violent offenses. Class 1 is characterized by a 100% probability of drug offenses and a slight probability (14.5%) of having a weapons offense in their history. The theft and nonviolent offenses class (Class 2) had moderate probabilities of public nuisance/ traffic offenses (9%), DUI (9%), theft

(25%), burglary (9%), and weapons offenses (8%). Class 3 had moderate probabilities of violent offenses (36%), public nuisance/ traffic offenses (12%), theft (25%), burglary (11%), drug offenses (20%), and a 100% probability of weapons offenses. Class 4 had a 100% probability of violent offenses and a moderate 23% probability of weapons offenses.

Figure 5.1. Probabilities of Item Endorsement for the Four Classes Retained by the Best Fitting Model

Table 5.2 shows the estimated proportions of class membership. The theft and nonviolent offenses class comprised an estimated 38.5% of the sample in New Orleans and represented the largest class. The multiple types class was the smallest class at an estimated 9.2% of the sample.

Table 5.2. Estimated Proportion of Class Membership

Class	Count	Proportion
Drug offenses	397.58	15.3%
Theft and nonviolent offenses	1001.03	38.5%
Multiple types	239.27	9.2%
Violent offenses	963.11	37.0%

Class Predictors In addition to establishing meaningful classes, we used a 3-step method to examine predictors of class membership using multinomial logistic regression.[39] The results in Table 5.3 show that gender was associated with class membership across all models, as males had significantly higher odds of being in the multiple types class compared to the drug offenses class ($OR = 8.64$). Race was also significantly associated with class membership, with white

individuals having significantly lower odds of being in the multiple types and violent offense class compared to the drug offenses class. Finally, both the post-implementation 1 and post-implementation 2 cohorts had significantly higher odds of being in the theft and nonviolent offenses and violent offenses classes when compared with the drug offense class. This finding suggests individuals primarily charged with drug offenses are booked less often since the beginning of SJC strategies in New Orleans.

Table 5.3. Multinomial logistic regression predicting class membership from gender, race, SJC implementation period, and relative deprivation

Variable	Odds Ratio	95% CI	P-value
Theft and nonviolent offenses (Class 2)			
Gender (Female)	.56	[.42, .75]	<.001***
Race (Non-White)	.86	[.65, 1.13]	.27
Groups (Pre-implementation)	1.27	[1.11, 1.45]	<.001***
Relative Deprivation	1.0	[.97, 1.03]	.98
Multiple types (Class 3)			
Gender (Female)	8.64	[.99, 75.17]	<.001***
Race (Non-White)	.31	[.15, .64]	.001**
Groups (Pre-implementation)	.92	[.73, 1.16]	.47
Relative Deprivation	1.04	[.98, 1.09]	.20
Violent offenses (Class 4)			
Gender (Female)	.53	[.39, .71]	<.001***
Race (Non-White)	.75	[.56, .99]	.04*
Groups (Pre-implementation)	1.69	[1.48, 1.93]	<.001***
Relative Deprivation	1.01	[.98, 1.05]	.45

Note: Reference categories are in parentheses.

Recidivism by Class We first applied a model using a distal outcomes regression approach to test whether class membership was associated with recidivism. However, the model did not converge. Therefore, we assigned classes to individuals based on their most likely class membership. While assigning classes directly to individuals does introduce some error since class membership is based on a probability scale, the 4-class solution we present here has high entropy (.92) and high average posterior probabilities (>.7). These two statistics indicate that there is minimal risk of misclassification and good separation of classes and, therefore, assigning class membership to individuals introduced minimal risk of misestimation.

Table 5.4 shows the results of the multinomial regression model predicting one-year recidivism by class membership. Results show that the multiple types group had 2.61 times the odds of recidivism at 1 year following their initial booking compared to the drug offenses class.

Table 5.4. Multinomial Logistic Regression

	B	ExpB	SE	Z
Intercept	-1.12	0.32	0.11	-9.87***
Class (Drug Offenses)				
Theft and nonviolent offenses	-0.09	0.91	0.14	-0.66
Multiple types	0.96	2.61	0.17	5.64***
Violent offenses	-0.42	0.66	0.14	-2.98**

Lucas County

Model Fit and Selection Table 5.5 shows model fit indices for LCA models testing k number of classes. For Lucas County, each of the models tested showed declining AIC and aBIC values. Further, statistically significant LMR values indicated that each added class improved model fit compared to the model with one fewer class. Entropy values for each of the 5 models were above the .8 threshold suggesting strong classification accuracy. While each of the 5 models showed adequate model fit, we found that both the 4 and 5 class models included a class with a proportion under 5%. The 3-class solution presented the most parsimonious solution with good entropy values (.91) and average posterior probabilities (>.9).

Table 5.5. Three Class Model was Retained as Best Fitting Solution

Number of Classes	AIC	aBIC	Entropy	LMR
1	19242.73	19264.81		
2	18036.57	18083.48	0.94	1207.26***
3	17869.43	17941.17	0.91	182.59***
4	17742.21	17838.78	0.91	143.22***
5	17669.27	17790.68	0.89	89.68***

Figure 5.2 shows probabilities of item endorsement for each of the eight items in the LCA model. Three classes were retained including a (1) DUI class where there was a 100% probability of having a DUI charge with low probabilities of other offenses; (2) a violent offenses class where violent offenses overall (100%) and domestic violence offenses (46%) separated this class from the others; and (3) a nonviolent offenses class where members exhibited moderate probabilities of public nuisance (24%), traffic (20%), theft (19%), and drug offenses (24%).

Table 5.6 shows estimated proportions of class membership in each of the 3 classes retained by the model. The largest class by count and proportion was the nonviolent offenses class that constituted an estimated 63% of the sample.

Figure 5.2. Probabilities of Item Endorsement for the Four Classes Retained by the Best Fitting Model

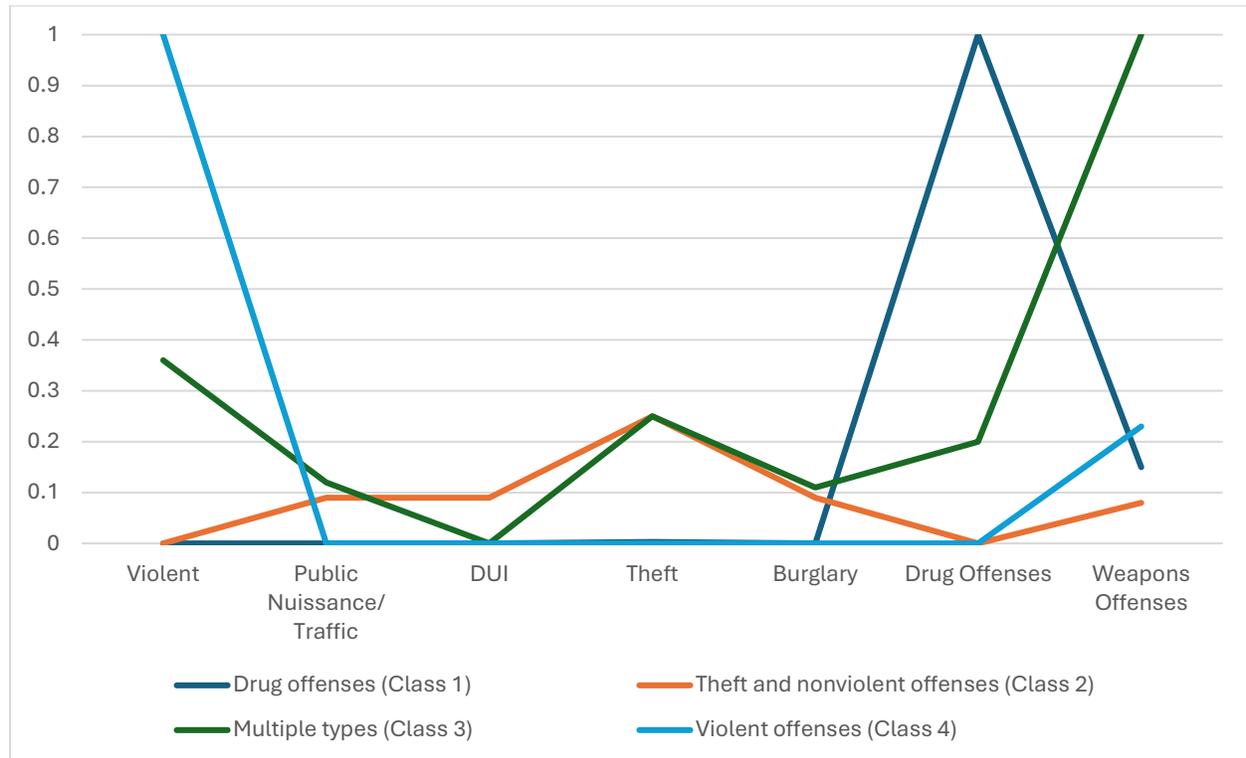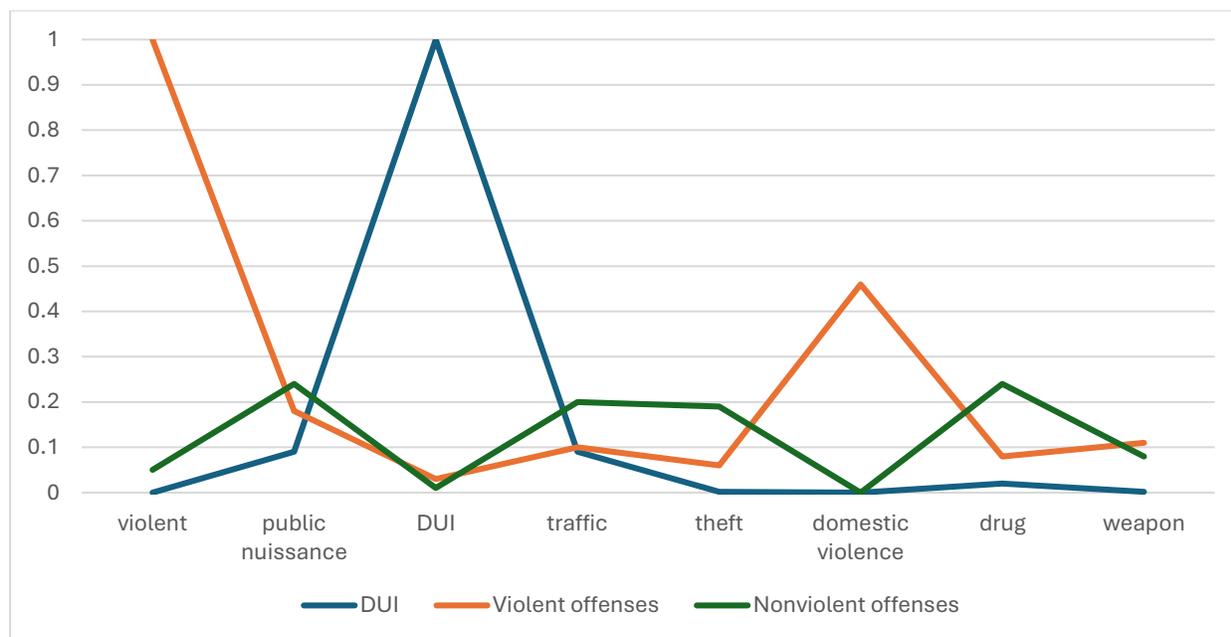**Table 5.6. Estimated Proportion of Class Membership**

Class	Count	Proportion
DUI	199.22	7.0%
Violent offenses	836.70	29.9%
Nonviolent offenses	1762.08	63.0%

Class Predictors Table 5.7 shows a 3-step approach to estimate a multinomial regression predicting class membership from gender, race, SJC implementation period (pre-, post-implementation 1, post-implementation 2), and relative deprivation. The DUI class was the reference category. White individuals had significantly lower odds of being in the violent offenses ($OR = .45$) and nonviolent offenses class ($OR = .61$) compared to the DUI class. Similar to the findings in New Orleans, the data here indicates that compared to the pre-implementation, SJC post-implementation 1 and post-implementation 2 groups had significantly higher odds of being the in the violent offenses class ($OR = 1.33$) than the DUI class. An increase in the relative deprivation index was associated with lower odds of being in the violent offenses class ($OR = .92$) and in the nonviolent offenses class ($OR = .88$) as compared to the DUI class.

Recidivism by Class We used a 3-step approach to estimating the impact of class membership on recidivism (see Table 5.8). The data indicated that those in the DUI class were significantly less likely to recidivate in the one year after their initial booking compared to the violent offenses and nonviolent offenses classes. The violent offenses class had a similar probability of recidivism as the nonviolent offenses class (44% vs. 40%).

Table 5.7. Multinomial logistic regression predicting class membership from gender, race, SJC implementation period, and relative deprivation

Variable	Odds Ratio	95% CI	P-value
Violent offenses			
Gender (Female)	.91	[.62, 1.35]	.65
Race (Non-White)	.45	[.32, .64]	<.001***
Groups (Pre-implementation)	1.33	[1.11, 1.60]	.003**
Relative Deprivation	.92	[.90, .95]	<.001***
Nonviolent offenses			
Gender (Female)	.68	[.47, .99]	.04*
Race (Non-White)	.61	[.44, .85]	.003**
Groups (Pre-implementation)	1.002	[.84, .1.20]	.99
Relative Deprivation	.88	[.86, .89]	<.001***

Note. Reference categories in parentheses.

Table 5.8. Mean differences in the probability of recidivism by class membership

Class	Proportion	SE
DUI	.23	.04
Violent offenses	.44	.02
Nonviolent offenses	.40	.01
χ^2	27.86***	

Key Takeaways, Latent Class Analysis

In both sites, **we were able to identify specific classes of individuals based on their offending patterns** in the initial case and the preceding year. Analyses indicate that **those in the classes related to substance use**—drug charge class in New Orleans, DUI class in Lucas County—**are less likely to be rebooked in both sites**. This may suggest that SJC (or other) strategies have more effectively targeted the issues underlying offenses related to substance use. It could also be that the decrease in the use of jail for less serious offenses documented in Chapter 1 is reflected in these findings.

Chapter 6
Discussion

In general, our findings suggest that jurisdictions can safely decrease jail populations without undermining community safety. Despite rhetoric linking the criminal justice reforms of recent years to crime spikes—real or imagined—this study found no evidence that the jail reduction reforms adopted in these sites led to increases in violent crime. In fact, the findings show *less* recidivism in the post-reform periods across all charge levels. The well-established damages created by overreliance on jail—including exposure to violence, trauma, and harm to the mental health of those detained in jails to financial and structural costs to families and communities[40]—can be minimized by strategies like the ones implemented in these sites without the feared rising crime rates.

Overall, our findings suggest that the implementation of SJC strategies in these sites was followed by significant reductions in jail bookings *without* increased risk to community safety. Specifically, both sites saw a decline in recidivism in the latest post-implementation period, including lower levels of *violent* recidivism.

Not only did the sites experience a steady decline in jail bookings over the study period, but those booked in the post-implementation periods were significantly more likely to avoid jail time altogether (i.e., spend less than a day in jail). In the context of declining jail bookings overall, the findings also indicate that those who were booked following SJC implementation were booked on charges more likely to be seen as "serious" (i.e., felonies and violent charges) and/or have a more serious (i.e., felony) recent criminal history. While the sites successfully pushed jail populations down, this suggests that some types of charges were still likely to result in jail time.

These findings have several practical implications for practitioners and jail reform efforts:

- Racial disparities persisted in these sites even as bookings overall declined. While booking trends showed a decline among white and BIPOC individuals throughout the study period, bookings were twice as likely to involve BIPOC individuals than white individuals in both sites. General movement to reduce jail populations is not sufficient to reduce racial disparities in those populations. As previous research on SJC strategies has shown, adopting strategies that successfully cut the number of people in jail does not *necessarily* eliminate racial disparities—in some cases, such efforts have even exacerbated disparities.[41] Jurisdictions must intentionally develop strategies targeting these disparities—for example, by using data to identify whether there are specific charge categories that drive disproportionate bookings for Black individuals and developing targeted strategies for those charges.

- A validated risk assessment can support decision makers—judges, prosecutors, community corrections, and others—to make informed decisions about setting bail, conscientious use of detention, and appropriate supervision and service connections. These tools can help jurisdictions prioritize who remains in custody while moving to reduce jail populations overall. The strategies implemented in these sites (including decision making informed on a validated risk assessment tool) reduced the use of jail without endangering public safety.

- Limit jail stays where possible. Shorter time in custody is linked to lower recidivism. This finding are informative not only for sentencing, but for pretrial decision making.

- The approaches implemented in these sites may be particularly promising for those with underlying substance use issues (drug charges in NOLA; DUI in Lucas County). Further exploration of the local strategies and resources specific to the needs of these populations may be informative for targeted recidivism reductions.

- Higher recidivism rates among individuals in the "generalist" categories—i.e., those facing a diverse range of criminal charges at booking—may suggest a need for additional programming to address root causes of criminal behavior. Again, further exploration of the specific strategies and resources implemented in these sites may shed light on areas for improvement in working with those who have more of a generalist charge history.

Study Limitations

There are several study limitations of note. Some of these limitations led to recalibrations of the methodology implemented throughout the study and circumscribed the conclusions we can draw. The way in which SJC was implemented in these sites involved several strategies simultaneously or near-simultaneously rolled out. Moreover, the SJC implementation occurred alongside other major national shifts potentially impacting jail populations—including other simultaneous jail reform efforts, the COVID-19 pandemic (and resultant push to reduce jail populations for public health reasons), and the far-reaching public outcry following the death of George Floyd. Consequently, it is not possible to directly link observed changes in jailing or criminal charges to any specific SJC strategy.

We originally intended to incorporate a novel approach to measuring criminal trajectory. By looking at the severity of charges on which individuals were booked, we hoped to determine whether there was a decrease (or increase) in *severity* of criminal charges over time, even among those who continued to be booked on new charges. However, the overall recidivism rates over the post-implementation 2 period were too low to support this type of analysis.

In addition, there were several data limitations of note. First, the data collected by the sites does not always support analyses of specific strategies. For instance, we did not have PSA scores for both sites, despite both New Orleans and Lucas County implementing the PSA. While we

incorporated many of the components of the PSA calculation into the multivariate models, we were not able to include the exact scores as we originally intended (with a proxy score to be calculated for the pre-implementation groups).

Both the criminal history and recidivism periods were limited, with one year on either side of the initial case for the full sample and up to two years of criminal history and recidivism for some of the sample. Ideally, we would have had two years for the full sample—possibly even longer for criminal history. This is a common limitation of recidivism studies and the COVID-19 pandemic exacerbated the issue. That is, because we know that COVID-19 was accompanied by declines in bookings across the country, drawing either criminal history or recidivism from March 2020 until the end of the COVID-19 lockdowns necessarily skews findings.

The measures of relative deprivation are linked to geography, which came with challenges. The available geographic data was provided by the court at the zip code level; we know that a zip code can be fairly large and Census tracts would have been a more precise measure.

Endnotes

[1] E.g., see CUNY Institute for State and Local Governance. 2021. *Jail Decarceration and Public Safety: Preliminary Findings from the Safety and Justice Challenge*. New York, NY: ISLG. Dabruzzo, D. *New Jersey Set Out to Reform Its Cash Bail System. Now, the Results Are In*. Houston, TX: Arnold Ventures. The Philadelphia District Attorney's Office. 2019. *Prosecutor Led Bail Reform: Year One Transparency Report*. Khan, S., E. West, and S. Rosoff. 2024. *Lowering Jail Populations Safely Before, During, and After COVID-19: Updated Findings on Jail Reform, Violent Crime, and the COVID-19 Pandemic*. New York, NY: ISLG. Lander, B. 2022. *NYC Bail Trends Since 2019*. New York, NY: NYC Comptroller. Philadelphia, PA: Philadelphia District Attorney's Office. Stemen, D. and D. Olson. 2020. *Dollars and Sense in Cook County: Examining the Impact of General Order 18.8A on Felony Bond Court Decisions, Pretrial Release, and Crime*. Chicago: Loyola University Chicago.

[2] E.g., See the FBI's Quarterly Uniform Crime Report (UCR), Q2, January-June 2024.

[3] More information on the PSA, including factors and scoring, can be found here.

[4] More information here.

[5] See quarterly ADPs figure and information on additional SJC strategies here.

[6] The initial sites joined the challenge in 2015, with implementation beginning in 2016.

[7] U.S. District Court for the District of Columbia - 416 F. Supp. 119 (D.D.C. 1976)

[8] E.g., see article here; Watson, Joe. 2016. "Judge Orders Ohio County to Cap Jail Population, Release Prisoners." *Prison Legal News,* March 1. Retrieved September 26, 2025.

[9] DLR Group, SSOE, and Chinn Planning. 2014. *New Jail Feasibility Study, Lucas County, Ohio*. Final Report.

[10] We also excluded all the following top charges that did not have a specific category but kept them in if they were part of someone's criminal history or a future arrest: Warrant, Hold, Probation Violation, Parole Violation, Writ for Criminal District Court, Detainer, Commitment, Contempt of Court, Constructive Contempt, Capias Juvenile, DNA Before Release, Commitment-State, Warrant State, Attachment-State, Attachment-Juvenile, Ice Detainer, Simple Escape from Custody, Writ-NA, and Warrant-Juvenile.

[11] We created the samples by selecting individuals based on their first booking (i.e., their initial case) in one of the sample years. For NOLA: 2017, 2019, and 2021; for Lucas County: 2015, 2017, and 2022.

[12] The NOLA sample includes 8,255 pre-implementation; 6,091 post-implementation 1; 3,360 post-implementation 2.

[13] The Lucas County sample includes 13,354 pre-implementation; 11,656 post-implementation 1; 9,127 post-implementation 2.

[14] To compare the pre- and two post-implementation samples, we conducted descriptive analyses and utilized chi-square tests to detect significant differences between the pre- and post-implementation groups. Due to the large sample size, small differences between the raw percentages rise to the level of statistical significance. Accordingly, we also looked at Cramer's V effect sizes.

[15] Initial booking charges include the top charge on the index booking resulting in inclusion in the sample.

[16] Criminal histories were measured up to two years before the initial booking. We were limited to a two-year time period given data availability for the pre-SJC sample.

[17] Booking dispositions were not included in Lucas County data.

[18] For analytical purposes, we defined the effective PSA implementation to be one year beyond the initial rollout date.

[19] For New Orleans, data on race were limited and only included white and BIPOC.

[20] See here for more information.

[21] We made the decision to collapse the race category because 96% of bookings in the Lucas County data during the study period involved Black or white individuals. At the highest monthly level, an "Other race" category would represent less than 100 bookings which did not affect either the model or the interpretation of the data.

[22] We used the formula to calculate the RRI described here.

[23] Relative deprivation is a zip code level variable obtained using the 2022 American Community Survey available from the U.S. Census. Neighborhood indicators of income, education, employment, and housing quality were used to create a composite score with higher scores indicating higher levels of neighborhood level deprivation. For our purposes, relative deprivation captures the geographic area at the zip code level in which an individual lives.

[24] Violent offenses categories were determined by ISLG and coded in the ISLG SJC data holdings based on the specifics of charging in each site.

[25] E.g., The JFA Institute. 2023. *The Impact of COVID-19 on Crime, Arrests, and Jail Populations: An Expansion on the Preliminary Assessment*. Denver, CO: The JFA Institute. Minton, T. D., Z. Zeng, L.M. Maruschak. 2021. *Special Report: Impact of COVID-19 on the Local Jail Population, January-June 2020*. Washington, DC: Bureau of Justice Statistics.

[26] E.g., Petrich, D.M., T.C. Pratt, C.L. Jonson, F.T. Cullen. 2021. "Custodial Sanctions and Reoffending: A Meta-Analytic Review." *Crime and Justice* 50:353-424. https://doi.org/10.1086/715100

[27] Data for a complete two-year timeframe was not available for the post intervention cohort at either study site. Therefore, the two-year follow up will only include two groups: the pre-intervention and post-intervention 1.

[28] Criminal history measured as bookings within the past two years.

[29] For detailed results, see Appendix E.

[30] Criminal history was capped at one year preceding the initial case for all one-year recidivism analyses and capped at two years preceding the initial case for all two-year recidivism analyses.

[31] Public nuisance and traffic offenses were combined to make one category. This was done after initial model convergence issues due to a low incidence rate of the two separate categories.

[32] Muthén, B.O., & L.K. Muthén. 2000. "Integrating Person-Centered and Variable-Centered Analyses: Growth Mixture Modeling with Latent Trajectory Classes." *Alcoholism: Clinical and Experimental Research* 24(6):882-891.

[33] Weller, B. E., Bowen, N. K., and Faubert, S. J. 2020. "Latent Class Analysis: A Guide to Best Practice". *Journal of Black Psychology* 46:4, 287-311.

[34] Nylund, K. L., T. Asparouhov, and B.O. Muthén. 2007. "Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study." *Structural Equation Modeling: A Multidisciplinary Journal* 14(4):535-569.

[35] Celeux, G., and G. Soromenho. 1996. "An Entropy Criterion for Assessing the Number of Clusters in a Mixture Model." *Journal of Classification* 13:195-212.

[36] Weller, B.E., N.K. Bowen, and S.J. Faubert. 2020. "Latent Class Analysis: A Guide to Best Practice." *Journal of Black Psychology* 46(4):287-311.

[37] Lo, Y., N.R. Mendell, and D.B. Rubin. 2001. "Testing the Number of Components in a Normal Mixture." *Biometrika* 88(3):767-778.

[38] For more information on distal outcomes regression approach see Lanza, S.T., X. Tan, and B. Bray. 2013. "Latent Class Analysis with Distal Outcomes: A Flexible Model-Based Approach." *Structural Equation Modeling* 29(20):1-26.

[39] See Lanza, S. T., X. Tan, & B.C. Bray. 2013. "Latent Class Analysis with Distal Outcomes: A Flexible Model-Based Approach." *Structural Equation Modeling 20*(1):1-26. https://doi.org/10.1080/10705511.2013.742377

[40] E.g., Craigie, T.A, A. Grawert, and C. Kimble. *Conviction, Imprisonment, and Lost Earnings: How Involvement with the Criminal Justice System Deepens Inequality*. New York: New York University School of Law, Brennan Center for Justice; Vallas, R., and S. Dietrich. 2014. *One Strike and You're Out: How We Can Eliminate Barriers to Economic Security and Mobility for People with Criminal Records*. Washington, DC: Center for American Progress; Petrich, D.M., T.C. Pratt, C.L. Jonson, F.T. Cullen. 2021. "Custodial Sanctions and Reoffending: A Meta-Analytic Review." *Crime and Justice* 50:353-424. https://doi.org/10.1086/715100; Listwan, S.J., C.J. Sullivan, R. Agnew, F.T. Cullen, & M. Colvin. 2011. "The Pains of Imprisonment Revisited: The Impact of Strain on Inmate Recidivism." *Justice Quarterly*, *30*(1), 144–168. https://doi.org/10.1080/07418825.2011.597772; Quandt, K.R. and A. Jones. 2021. *Research Roundup: Incarceration can Cause Lasting Damage to Mental Health*. Northampton, MA: Prison Policy Institute; Elderbroom, B., P. Mayer, F. Rose. 2025. *We Can't Afford It: Mass Incarceration and the Family Tax*. Fwd.Us.

[41] E.g., Stemen, D., R. Dunlea, M. Pearson, and B.L. Kutateladze. 2024. *Time to Disposition in Felony Cases: A Research and Policy Brief*; Huerter, R. and A. Krider. 2024. *Creating Data-Informed Strategies to Understand the Needs of People in Your Jail*. Troy: Policy Research, Inc.; Pettus, C. B.M. Huebner, F.S. Taxman, T. Sanders, L. Lightfoot, N. McCarthy, and R. Bennett. 2024. *Achieving Racial Equity and Improving Culture in Jails Using a Community-Engaged Quality Improvement Process*. Weill, J., A.B. Cissner, S. Naraharisetti. 2022. *Population Review Teams: Evaluating Jail Reduction and Racial Disparities Across Three Jurisdictions*.

Appendix A. Booked Population Descriptives
by Time Period and Site

Table A.1. Differences Between Pre- and Post-SJC Implementation Populations (New Orleans)

	Pre-SJC (2017) 8,255		Post-SJC 1 (2019) 7,245		Post-SJC 2 (2021) 4,574		
N	N	%	N	%	N	%	Effect Size[1]
Demographics							
Male	6,405	78%	5,615	78%	3,504	77%	.01
Black[2]	6,434	78%	5,822	80%	3,822	84%	.05***
Average Age	34		35		35		
Current Booking Charge[3]							
Top Charge Category							
Person	2,977	36%	2,817	39%	2,391	52%	.13***
Property	891	11%	823	11%	616	14%	.03***
Drug	1,576	19%	1,463	20%	399	9%	.12***
DUI	606	7%	57	1%	12	0%	.19***
Theft[4]	476	6%	450	6%	245	5%	.01
Public Nuisance	372	5%	401	6%	81	2%	.07***
Traffic	62	1%	24	0%	9	0%	.04***
Other	1,230	15%	1,221	17%	970	21%	.06***
Charge Flags							
Any Violent Charge	2,994	36%	2,757	38%	2,207	48%	.10***
Any Weapons Charge	421	5%	371	5%	314	7%	.03***
Charge Severity							
Felony Top Charge	5,499	67%	4,702	65%	3,128	68%	.03***
Misdemeanor Top Charge	2,756	33%	2,543	35%	1,446	32%	.03***
Disposition[5]							
No Action	1,373	17%	2,046	28%	553	12%	.20***
Release on Recognizance	1,749	21%	1,251	17%	828	18%	
Bail Bond	3,184	39%	2,328	32%	2,779	61%	
Transfer	396	5%	283	4%	42	1%	
Sentenced	520	6%	247	3%	63	1%	
No Release	1,021	12%	1,088	15%	307	7%	
Criminal History[6]							
Any Prior Booking[7]	1,982	24%	2,128	29%	1,211	27%	.05***
Any Prior Violent Booking	1,042	13%	1,173	16%	741	16%	.05***
Any Prior Felony Booking	1,775	22%	1,903	26%	1,090	24%	.04**
Any Prior Misdemeanor Booking	1,423	17%	1,596	22%	912	20%	.05***

*p < .05, **p < .01, ***p < .001

[1] Cramer's V was used to determine effect size. All variables have little (<.1) to low (.1 to .3) association.

[2] The demographic is Black/White. Other categories were not available.

[3] Top charge categories do not equal 100% due to rounding.

[4] Incudes theft not related to property, such as fraud

[5] Categories are not dichotomous.

[6] In the two years prior to the instant case.

[7] Because some individuals have multiple prior arrests, the total felony + misdemeanor priors are > total prior arrests. Prior violent charges may be either felony or misdemeanor level charges.

Table A.2. Differences Between Pre- and Post-SJC Implementation Populations (Lucas County)

	Pre-SJC (2015) 13,354		Post-SJC (2017) 11,656		Post-SJC (2022) 9,127		
N	N	%	N	%	N	%	Effect Size[1]
Demographics							
Male	10,102	76%	8,689	75%	6,695	73%	0.02***
Race							0.04***
Black	6,276	47%	5,603	49%	4,802	53%	
White	6,502	49%	5,507	48%	3,871	43%	
Latino	438	3%	442	4%	305	3%	
Other	26	0%	10	0%	17	0%	
Average Age	34		35		36		
Current Charge[2]							
Top Charge Category							
Person	1,801	14%	1,647	15%	1,405	16%	.03***
Property	1,140	9%	1,058	9%	696	8%	.02***
Drug	1,912	15%	1,661	15%	901	10%	.06***
DUI	919	7%	837	7%	627	7%	.01
Theft[3]	1,200	9%	1,144	10%	732	8%	.02***
Public Nuisance	1,880	14%	1,381	12%	1,067	12%	.03***
Traffic	1,584	12%	1,127	10%	648	7%	.06***
Other	4,256	33%	3,794	34%	2,594	30%	.03***
Charge Flags							
Any Violent Charge	2,885	22%	2,646	23%	2,735	31%	.09***
Any Weapons Charge	525	4%	460	4%	670	8%	.07***
Charge Severity							
Felony Charge	4,406	34%	4,462	40%	3,484	41%	.06***
Misdemeanor Top Charge	8,398	66%	6,796	60%	5,006	59%	.06***
Criminal History[4]							
Any Prior Booking[5]	6,126	46%	5,546	48%	3,620	40%	.06***
Any Prior Violent Booking	1,963	15%	1,936	17%	1,464	16%	.02***
Any Prior Felony Booking	2,827	21%	2,996	26%	2,007	22%	.05***
Any Prior Misdemeanor Booking	4,904	37%	4,135	36%	2,416	27%	.10***

*p <. 05, **p <. 01, ***p < .001

[1] Cramer's V was used to determine effect size. All variables have little (<.1) to low (.1 to .3) association.

[2] Top charge categories do not equal 100% due to rounding.

[3] Incudes theft not related to property, such as fraud

[4] In the two years prior to the instant case.

[5] Because some individuals have multiple prior arrests, the total felony + misdemeanor priors are > total prior arrests. Prior violent charges may be either felony or misdemeanor level charges.

Appendix B. Crime Trends Methodology

Seasonal Autoregressive Integrated Moving Average models with exogenous variables (SARIMAX) were estimated to examine trends and forecasting bookings in Lucas County while accounting for seasonality and the impact of other SJC programs that were implemented at the same time as the PSA and COVID-19. A SARIMAX model consists of both seasonal and nonseasonal auto regressive and moving average terms where appropriate. We fitted each SARIMAX model using the auto.arima procedure in R, which selects model parameters based on the lowest Akaike Information Criteria (AIC) values. Once a model was selected, we examined additional model fit criteria including the Ljung-Box test of residual independence and Auto Correlation Function (ACF) to ensure that the fitted models were appropriate. A total of five separate SARIMAX models were estimated including an overall sample, subsamples that included bookings for violent charges, nonviolent charges, and individuals identified as white and BIPOC. To forecast monthly bookings 24 months beyond the end of data collection, we estimated SARIMAX models for overall bookings. While Lucas County data showed evidence of seasonality, models for New Orleans did not. While we tested a model with a specified seasonal term, model fit indices showed that removing the seasonal term greatly improved model fit. Therefore, we did not specify seasonality in any of the New Orleans models.

In Lucas County, SJC kicked off officially in 2015 while the use of the PSA tool began around 2016. To model its effects, we defined the first period for the purposes of these analyses as the period between January 2017 and January 2020. We modeled in the effect of COVID-19 by examining the period in Lucas County when stay-at-home orders were in place. In Ohio, stay-at-home orders were mostly lifted by the end of May 2020. A second, post-COVID-19 implementation period was defined as the period from January 2022 until the end of the data collection period in April 2023. Dichotomous variables for each of these three periods were created and entered into the SARIMAX models as exogenous variables.

Monthly bookings were examined by whether the charge was for a violent or nonviolent offense, and by race defined as white and BIPOC. While data were available in Lucas County for a more granular examination of race/ethnicity, 96% of individuals were either white or Black. While we did consider a model that did include an other race category, results and interpretation of the model did not change from the model presented here. Further, the other category included a mix of Asian, Latino/a, and Native American individuals, which would not add to our understanding of the impact of race on booking trends in the two sites. Given that the conclusions arrived from the two approaches were identical and that the Other race category would not provide any meaningful insight, we opted to collapse race into two categories. In New Orleans, data on race was restricted to whether an individual was white or BIPOC.

For New Orleans, we took a similar approach and created a dichotomous variable that reflects PSA implementation dates in 2018 and a secondary implementation of 2021. For analytical purposes, we built in a one-year implementation period and used January 2019 as the

implementation start in New Orleans. Stay-at-home orders for COVID-19 were lifted in Louisiana at the end of May 2020.

Appendix C. Two-Year Recidivism Findings

Figure C.1. Predicted Probability of Recidivism at 2 Years (NOLA)

Bar chart showing predicted probability of recidivism at 2 years for NOLA:
- Felony Recidivism: Pre-Implementation 33.0%, Post-Implementation 1 38.4%
- Misdemeanor Recidivism: Pre-Implementation 11.4%, Post-Implementation 1 10.5%
- Violent Recidivism: Pre-Implementation 12.4%, Post-Implementation 1 15.7%

Legend: Pre-Implementation, Post-Implementation 1
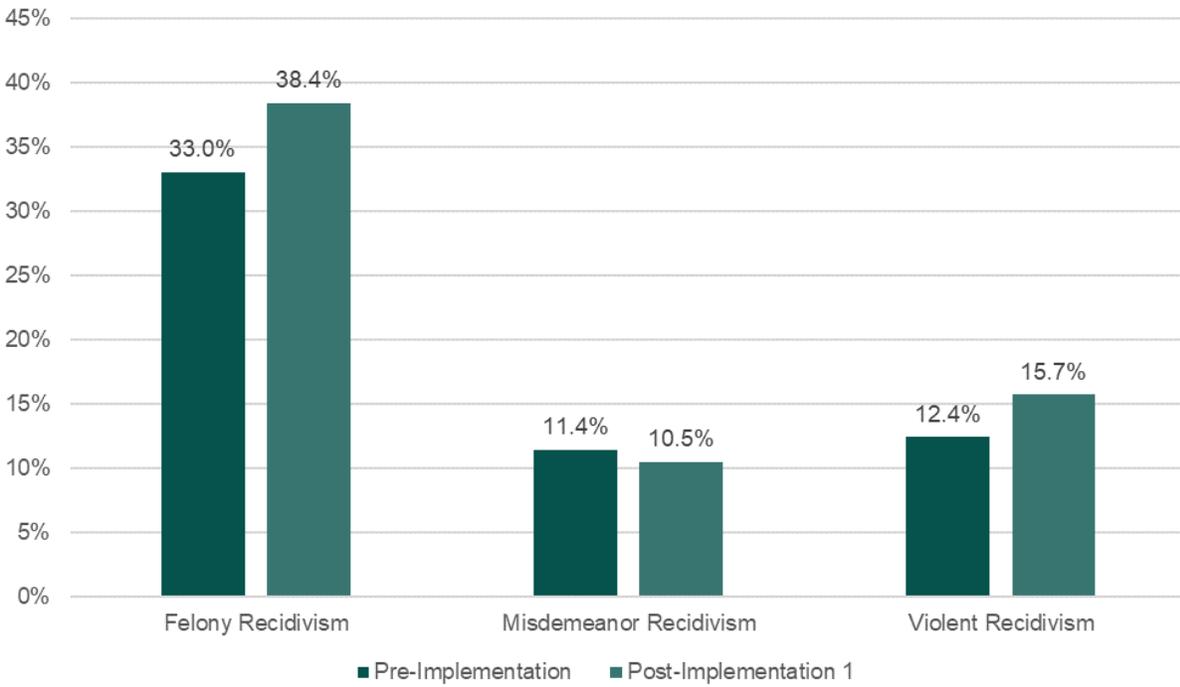
Figure C.2. Predicted Probability of Recidivism at 2 Years (Lucas Co.)

Bar chart showing predicted probability of recidivism at 2 years for Lucas Co.:
- Felony Recidivism: Pre-Implementation 27.3%, Post-Implementation 1 26.5%
- Misdemeanor Recidivism: Pre-Implementation 34.5%, Post-Implementation 1 34.6%
- Violent Recidivism: Pre-Implementation 18.0%, Post-Implementation 1 14.6%

Legend: Pre-Implementation, Post-Implementation 1
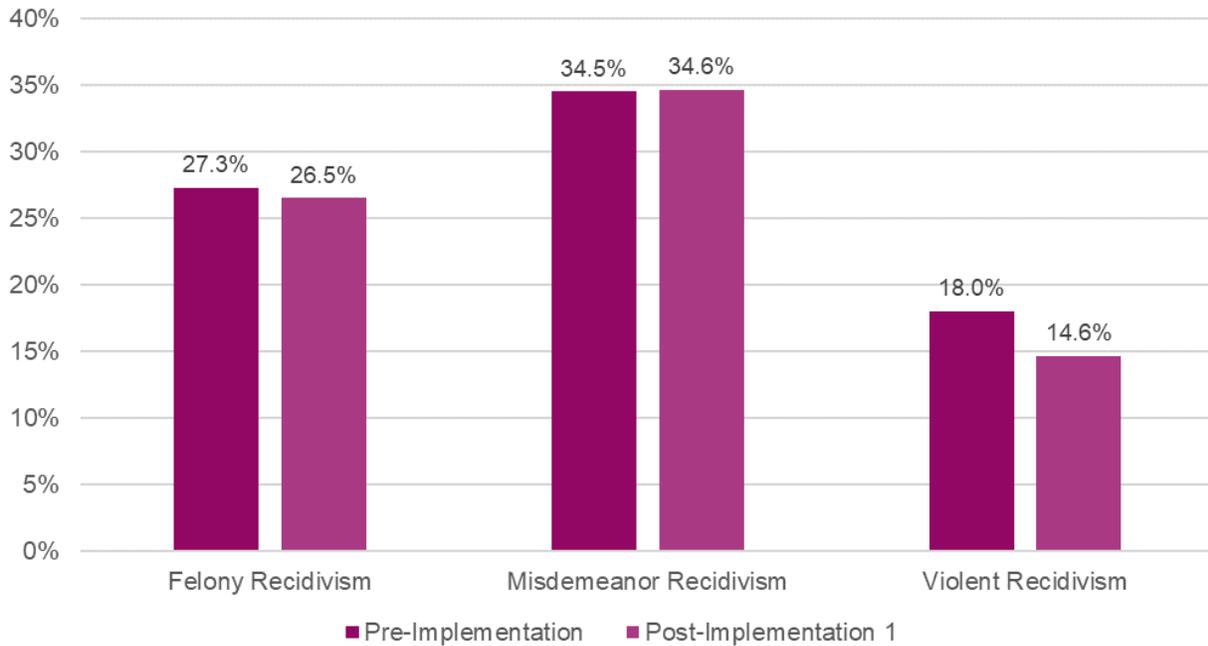
Appendix D. Regression Tables
Recidivism, Days in Jail

New Orleans

Table D.1. Logistic regression predicting 1- and 2-year felony recidivism from gender, race, age, SJC implementation period, prior misdemeanor, prior felony, relative deprivation, and days in jail – New Orleans

	1 Year Follow Up			2 Year Follow Up		
	B	SE	Exp(B)	B	SE	Exp(B)
Gender (Female)						
Male	0.77***	0.14	2.16	0.74***	0.13	2.09
Race (Nonwhite)						
White	-0.53***	0.16	0.59	-0.60***	0.15	0.55
Age	-0.01*	0.00	0.99	-0.01**	0.00	0.99
Group (Pre-Implementation)						
Post-Implementation 1	0.3**	0.12	1.37	0.33**	0.11	1.39
Post-Implementation 2	-1.36***	0.18	0.26			
Prior Misdemeanor	0.87**	0.27	2.39	0.63**	0.2	1.89
Prior Felony	1.2***	0.16	3.29	0.80***	0.14	2.24
Relative Deprivation	0.01	0.02	1.01	0.01	0.02	1.01
Days in Jail (None)						
Less than a week	0.25	0.15	1.28	0.27	0.14	1.31
More than a week	0.47**	0.18	1.60	0.67***	0.17	1.95
Intercept	-2.05**	0.63	0.13	-1.68***	0.60	0.19
AIC	2120.5			2163.3		

*** p < .001, ** p < .01, * p < .05

Table D.2. Logistic regression predicting 1- and 2-year misdemeanor recidivism from gender, race, age, SJC implementation period, prior misdemeanor, prior felony, relative deprivation, and days in jail – New Orleans

	1 Year Follow Up			2 Year Follow Up		
	B	SE	Exp(B)	B	SE	Exp(B)
Gender (Female)						
Male	-0.01	0.20	0.99	0.34	0.19	1.41
Race (Nonwhite)						
White	-0.2	0.24	0.82	-0.21	0.22	0.81
Age	-0.00	0.01	0.99	-0.00	0.01	0.99
Group (Pre-Implementation)						
Post-Implementation 1	-0.28	0.19	0.76	-0.10	0.15	0.90
Post-Implementation 2	-0.8***	0.24	0.45			
Prior Misdemeanor	1.10**	0.35	3.02	1.04***	0.23	2.83
Prior Felony	0.02	0.3	1.02	0.01	0.20	1.01
Relative Deprivation	0.04	0.03	1.04	0.03	0.02	1.03
Days in Jail (None)						
Less than a week	0.10	0.23	1.11	0.58*	0.23	1.78
More than a week	0.09	0.29	1.09	0.36	0.26	1.43
Intercept	-3.67***	1.01	0.03	-3.62***	0.91	0.03
AIC	1105.4			1226.4		

*** p < .001, ** p < .01, * p < .05

Table D.3. Logistic regression predicting 1- and 2-year violent recidivism from gender, race, age, SJC implementation period, prior misdemeanor, prior felony, and relative deprivation – New Orleans

	1 Year Follow Up			2 Year Follow Up		
	B	SE	Exp(B)	B	SE	Exp(B)
Gender (Female)						
Male	0.37	0.20	1.44	0.46*	0.18	1.58
Race (Nonwhite)						
White	-1.13***	0.30	0.32	-1.02***	0.25	0.36
Age	-0.01*	0.01	0.99	-0.02**	0.01	0.98
Group (Pre-Implementation)						
Post-Implementation 1	0.08	0.18	1.08	0.30*	0.14	1.36
Post-Implementation 2	-0.58*	0.22	0.56			
Prior Misdemeanor	1.16***	0.32	3.18	0.92***	0.22	2.50
Prior Felony	0.77***	0.23	2.17	0.05	0.18	1.05
Relative Deprivation	-0.01	0.03	0.99	0.01	0.02	1.01
Days in Jail (None)						
Less than a week	-0.07	0.21	0.93	0.15	0.19	1.16
More than a week	-0.52	0.28	0.59	0.10	0.22	1.10
Intercept	-1.81	0.93	0.16	-2.11*	0.84	0.12
AIC	1192.2			1396.6		

***p < .001, **p < .01, *p < .05

Table D.4.Ordinal logistic regression predicting jail stays from gender, race, age, SJC implementation period, prior misdemeanor, prior felony, and relative deprivation – New Orleans

	1 Year Follow Up		
	B	SE	Exp(B)
Gender (Female)			
Male	0.69***	0.09	2.00
Race (Nonwhite)			
White	-0.34***	0.10	0.71
Age	0.01	0.00	1.01
Group (Pre-Implementation)			
Post-Implementation 1	-0.14	0.09	0.87
Post-Implementation 2	-0.54***	0.09	0.58
Prior Misdemeanor	0.25	0.22	1.28
Prior Felony	1.11***	0.12	3.03
Relative Deprivation	0.01	0.01	1.01
Intercept			
None/Less than a week	-0.56	0.41	
Less than a week/Less than 1 month	2.19***	0.41	
Less than 1 month/ Less than 90 days	2.83***	0.41	
Less than 90 days/ More than 90 days	3.55***	0.41	

***p < .001, **p < .01, *p < .05

Lucas County

Table D.5. Logistic regression predicting 1- and 2-year felony recidivism from gender, race, SJC implementation period, prior misdemeanor, prior felony, relative deprivation, and days in jail – Lucas County

	1 Year Follow Up			2 Year Follow Up		
	B	SE	Exp(B)	B	SE	Exp(B)
Gender (Female)						
Male	0.42**	0.14	1.52	0.40**	0.14	1.50
Race (Nonwhite)						
White	-0.37**	0.13	0.69	-0.43***	0.13	0.65
Age	-0.02**	0.01	0.98	-0.02***	0.01	0.98
Group (Pre-Implementation)						
Post-Implementation 1	0.01	0.14	1.01	0.07	0.12	1.07
Post-Implementation 2	-0.38*	0.15	0.69			
Prior Misdemeanor	0.02	0.13	1.02	0.35**	0.12	1.42
Prior Felony	1.21***	0.13	3.34	1.31***	0.13	3.69
Relative Deprivation	0.01	0.01	1.01	0.02	0.01	1.02
Days in Jail (None)						
Less than a week	0.13	0.14	1.14	0.15	0.15	1.17
More than a week	0.53***	0.16	1.70	0.44**	0.16	1.56
Intercept	-1.80***	0.51	0.17	-1.89***	0.52	0.15
AIC	2001.5			2008.1		

*** p < .001, ** p < .01, * p < .05

Table D.6. Logistic regression predicting 1- and 2-year misdemeanor recidivism from gender, race, SJC implementation period, prior misdemeanor, prior felony, relative deprivation, and days in jail – Lucas County

	1 Year Follow Up			2 Year Follow Up		
	B	SE	Exp(B)	B	SE	Exp(B)
Gender (Female)						
Male	0.26*	0.12	1.30	0.15	0.12	1.16
Race (Nonwhite)						
White	-0.24*	0.11	0.79	-0.23*	0.11	0.80
Age	0.00	0.01	1.00	0.00	0.01	1.00
Group (Pre-Implementation)						
Post-Implementation 1	0.02	0.12	1.02	0.09	0.11	1.09
Post-Implementation 2	-0.52***	0.13	0.59			
Prior Misdemeanor	1.09***	0.11	2.98	1.03***	0.11	2.79
Prior Felony	-0.01	0.14	0.99	-0.09	0.13	0.91
Relative Deprivation	0.02	0.01	1.02	0.03*	0.01	1.03
Days in Jail (None)						
Less than a week	0.05	0.12	1.05	0.22	0.13	1.24
More than a week	0.18	0.15	1.19	0.10	0.15	1.10
Intercept	-2.46***	0.46	0.09	-2.31***	0.46	0.10
AIC	2329.9			2119.7		

*** p < .001, ** p < .01, * p < .05

Table D.7. Logistic regression predicting 1- and 2-year violent recidivism from gender, race, SJC implementation period, prior misdemeanor, prior felony, relative deprivation, and days in jail – Lucas County

	1 Year Follow Up			2 Year Follow Up		
	B	SE	Exp(B)	B	SE	Exp(B)
Gender (Female)						
Male	0.91***	0.21	2.48	0.70***	0.18	2.02
Race (Nonwhite)						
White	-0.43**	0.16	0.65	-0.56***	0.15	0.57
Age	-0.01*	0.01	0.99	-0.01	0.01	0.99
Group (Pre-Implementation)						
Post-Implementation 1	-0.15	0.17	0.86	-0.16	0.14	0.85
Post-Implementation 2	-0.26	0.18	0.77			
Prior Misdemeanor	0.86***	0.15	2.37	0.80***	0.14	2.23
Prior Felony	0.13	0.18	1.14	0.25	0.15	1.28
Relative Deprivation	0.04*	0.02	1.04	0.05**	0.02	1.05
Days in Jail (None)						
Less than a week	0.36	0.19	1.44	0.09	0.17	1.09
More than a week	1.02***	0.20	2.78	0.37*	0.19	1.45
Intercept	-4.29***	0.68	0.01	-3.81***	0.65	0.02
AIC	1425.1			1423.1		

*** p < .001, ** p < .01, * p < .05

Table D.8. Ordinal logistic regression predicting jail stays from gender, race, SJC implementation period, prior misdemeanor, prior felony, and relative deprivation – Lucas County

	1 Year Follow Up		
	B	SE	Exp(B)
Gender (Female)			
Male	0.25**	0.09	1.29
Race (Nonwhite)			
White	0.32***	0.08	1.37
Age	0.01	0.00	1.01
Group (Pre-Implementation)			
Post-Implementation 1	-0.22*	0.09	0.82
Post-Implementation 2	-0.21*	0.09	0.81
Prior Misdemeanor	0.29**	0.08	1.33
Prior Felony	0.42***	0.11	1.52
Relative Deprivation	0.02*	0.01	1.02
Intercept			
None/Less than a week	0.32	0.32	
Less than a week/Week or more	2.63	0.33	

Appendix E. Cox Regression
Time to Recidivism

Table E.1. Cox Proportional Hazards Regression Predicting Time to Recidivism – New Orleans

	1 year			2 years		
	B	SE	HR	B	SE	HR
Gender (Female)						
Male	0.51***	0.11	1.67	0.52	0.10	1.68
Race (Nonwhite)						
White	-0.39***	0.12	0.68	-0.47***	0.11	0.63
Group (Pre-Implementation)						
Post-Implementation 1	0.03	0.09	1.03	0.09	0.07	1.09
Post-Implementation 2	-1.15***	0.11	0.32			
Prior Misdemeanor	0.79***	2.21	0.17	0.58***	0.12	1.79
Prior Felony	0.83***	2.29	0.11	0.61***	0.09	1.84
Relative Deprivation	0.01	0.01	1.01	0.00	0.01	1.00
Jail Stay	0.00	0.00	1.00	-0.00	.00	.99
Likelihood Ratio Test	$\chi^2 (8) = 268.7, p < .001$			$\chi^2 (7) = 147.7, p < .001$		
N	2,438			1,793		
Events	606			750		

Table E.2. Cox Proportional Hazards Regression Predicting Time to Recidivism - Lucas County

	1 year			2 years		
	B	SE	HR	B	SE	HR
Gender (Female)						
Male	0.15*	0.08	1.17	0.09	0.08	1.10
Race (Nonwhite)						
White	-0.06	0.94	0.94	-0.17*	0.07	0.85
Group (Pre-Implementation)						
Post-Implementation 1	-0.05	0.07	0.95	0.03	0.06	1.03
Post-Implementation 2	-0.16*	0.08	0.85			
Prior Misdemeanor	1.25***	0.07	3.51	0.92***	0.07	2.52
Prior Felony	0.98***	0.07	2.67	0.69***	0.07	2.00
Relative Deprivation	0.01	0.01	1.00	0.01	0.01	1.01
Jail Stay	0.00	0.00	1.01	-0.00	0.00	0.99
Likelihood Ratio Test	$\chi^2 (8) = 602.7, p < .001$			$\chi^2 (7) = 372.3, p < .001$		
N	2,445			1,724		
Events	1,033			957		