The Day After the Recall: Policing and Prosecution in San Francisco

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Abstract

Prosecutors' policies and decisions are often the subjects of high-profile political debates and research studies on crime and recidivism. However, the effect of prosecutor policies on crime can be confounded by any simultaneous changes in police behavior. This paper explores the effect of a District Attorney recall election on policing patterns following a contentious relationship between the prosecutor's office and the corresponding police department. With policing, prosecution, and jail data from San Francisco, we use an Interrupted Time Series (ITS) estimator with a kink at the recall election date to study how local prosecutor politics affect police behavior. We find that before the recall election of an "unfriendly DA," the police decreased its activity. Immediately following the successful recall, the police ramped up their efforts, increasing the local jail population. Our findings illustrate the importance of accounting for police departments' responses to prosecutorial politics when considering the effects of prosecutor policies on crime.

1 Introduction

District Attorneys (DAs) are the heads of the prosecutor's office. They are the elected officials who determine the jurisdiction's approach toward criminal justice policy. American prosecutors represent local jurisdictions and enjoy independence and a wealth of discretion in how criminal statutes are applied (Sklansky, 2018; Tonry, 2012). Typically, state prosecution is organized along county lines under the direction of an elected and autonomous prosecutor, designated as county attorney, district attorney, or state attorney. During the mass prison expansion between 1970 and 2000, the prosecutor's power has expanded considerably compared to judges, defense attorneys, and other actors in the criminal justice system (Simon, 2007).

In recent years, the politics of prosecutor elections have changed dramatically. It used to be common wisdom that prosecutor elections are apolitical: rarely contested (Pfaff, 2017; Wright, 2014; Bibas, 2016), and incumbents "win until they quit" (Bazelon, 2020). However, new studies point toward a change in trend. In a study of prosecutor elections in 200 high-population districts in the US between 2012 and 2020, Wright and others find that the likelihood that an incumbent would run unopposed "fell by roughly eight percent for each passing year." (Wright et al., 2021). Similarly, Hessick and Morse collected election results (2014 or 2016 cycle) for 2,315 districts across 45 states and found that in urban jurisdictions, elections were more likely to be contested and competitive (Hessick and Morse, 2019).

In addition, some new DAs and DA candidates recently began making political promises to transform the criminal justice system from within through new visions of the district attorney's job (Wright et al., 2021; Davis, 2019). Colloquially, reform-minded DAs are known as "progressive prosecutors." By the beginning of 2023, America's five biggest cities by population have elected progressive district attorneys (including Los Angeles, Philadelphia, Boston, New York, Chicago, and Houston) (Hessick and Morse, 2019).[1] A key tenet of the progressive prosecutor movement is police accountability (Sklansky, 2016, 2017); unintended consequences could emerge if, in response to heightened police accountability, public safety decreased. Furthermore, measuring the effect of progressive prosecutors' policies on crime may be confounded by any changes in police behavior that affect crime or crime reporting.

The changing nature of prosecutor politics, namely, the combination of increased competitiveness and attention from voters with a new political movement aimed at reform, might impact public safety unexpectedly due to its effect on police-prosecutor relationships. This relationship has been shown to affect police use of force (Stashko and Garro, 2023). Legal scholars, practitioners, and advocacy groups have advocated for regulatory measures that circumscribe the involvement

[1] New York has five district attorneys, one for each county/borough. New York County (Manhattan) and Kings County (Brooklyn) have elected progressive prosecutors.

of DAs in cases pertaining to local law enforcement officers. In the vast majority of jurisdictions, cases implicating local law enforcement personnel fall under the purview of the resident DA. This dynamic, coupled with the orientations of contemporary progressive prosecutors, presents salient legal and policy-related considerations.

In this paper, we investigate the implications of a contentious DA recall election on San Francisco's policing, underscoring how political dynamics can shape police outcomes. Utilizing an Interrupted Time Series (ITS) estimator, with a discontinuity at the recall date, we identify significant pre- and post-recall behavioral shifts. While there is a pre-election decline, post-election police activities such as stops and felony arrests notably surge. However, citizen-initiated interactions with law enforcement remain essentially unchanged. A secondary yet salient observation is the pre-election decrease and post-election ascent in jail populations. The sole behavioral alteration in the prosecutor's office is an uptick in post-recall dismissals, hinting at supply-driven changes in prison populations. To bolster our findings' robustness, we provide bandwidth sensitivity analysis and a placebo test employing prior-year data to support our conclusions further.

2 Related Literature

We explore in this paper a model of police performance in the context of prosecutor elections. Police officers might explicitly or implicitly react to an upcoming prosecutor election. Specifically, they are incentivized to affect the voters' perceptions of the incumbent's performance. If the incumbent is up for reelection, police officers might improve their performance to improve public perceptions of the incumbent's effect on public safety or lower their performance to achieve the opposite results. Historically, prosecutors and police departments were working hand-in-glove, but the recent reform movement disrupted this relationship as it introduced prosecutors more critical of police accountability.

The burgeoning literature on prosecutor-police dynamics hints at significant behavioral interdependencies. Specifically, a notable study indicates that police officers might recalibrate their use of lethal force following the ousting of an incumbent DA, potentially due to uncertainties surrounding new DA relationships (Stashko and Garro, 2023). Such ties often harbor conflicts of interest, with instances of questionable collaborations and campaign contributions underscoring the intricate nexus between prosecutors and law enforcement.[2] Our work augments this discourse by elucidating the profound implications of the police-prosecutor relationship on routine policing

[2]For instance, amidst an investigation involving the Fremont police union's leadership, DA Nancy O'Malley of Alameda County, California, received a \$10,000 donation from the union during her re-election campaign. The subsequent exoneration of the officers in question exemplifies these conflicts (Hessick and Rossi, 2018). The resultant calls for campaign finance reforms stem from perceived erosion in public trust and concerns over systemic shortcomings in addressing police misconduct (Westervelt, 2020).

outcomes and its cascading effects on citizens' incarceration tendencies.

Previous studies utilizing comparable research designs have delved into how policing behaviors shift post-events like high-profile police shootings or subsequent protests. Evidence suggests transient reductions in police stops post such incidents, with no corresponding short-term crime spikes (Shjarback et al., 2017; Abrams et al., 2022; Cho et al., 2021). Post George Floyd's murder, Minneapolis police exhibited a marked discontinuity in reporting race and gender data during stops—a decline from roughly 71% to 35%, a decrease of approximately 36 percentage points (United States Department of Justice, Civil Rights Division and United States Attorney's Office, District of Minnesota, Civil Division, 2023). Our research underscores the responsiveness of policing to political landscapes, especially concerning calls for police accountability from prosecutorial entities. Numerous studies have delved into the nexus between accountability frameworks and police efficacy. While some found evidence of "de-policing" after the establishment of community oversight bodies or in the wake of external controversies (Ali and Nicholson-Crotty, 2021; Mikdash, 2022; Ba and Rivera, 2019), others indicate crime surges following governmental inquiries into high-profile police incidents (Devi and Fryer Jr, 2020). Furthermore, evidence suggests diminished arrest rates after targeted ambushes on officers (Sloan, 2019). Given these findings, we posit that evaluations of legal system shifts, such as the induction of a new DA or prosecutorial policy changes, necessitate thoroughly examining consequent arrest patterns and nuances.

Our study exploits the June election to estimate a change in police behavior across multiple outcomes. In addition, we also estimate downstream effects on the San Francisco jail population. An existing strand of literature documents the effects of pre-trial detention and other short jail stays on defendants' future outcomes. Defendants detained pre-trial are more likely to plead guilty, less likely to engage in pre-trial misconduct (because of incapacitation) but more likely to recidivate, and are less likely to earn formal-sector income, receive government benefits, or file taxes than their counterparts who are not detained (Dobbie et al., 2018). Furthermore, Black defendants sentenced to even short jail stays are less likely to vote following their incarceration sentences (White, 2019). To the extent that these effects hold in San Francisco, these transitory changes in the jail population due to police responses to local political events could substantially affect defendants' subsequent outcomes.

3 Background

Opposition combined with high (and often confused) expectations from voters poses significant challenges to the new wave of district attorneys (Davis, 2019; Cox and Gripp, 2021). In one study, interviews with assistant district attorneys (the rank-and-file prosecutors) in a progressive office described a legitimacy crisis (Cox and Gripp, 2021). Studies show that DAs are more punitive in an election year (Bandyopadhyay and McCannon, 2014; Dyke, 2007; Nadel et al., 2017; Okafor, 2021). This study explores the possibility of police officers' political opposition during a publicized conflict between San Francisco's progressive prosecutor and the SFPD before the prosecutor's recall election.

Documented incidents of excessive police violence against laypeople caused unprecedented protests against police violence in America and raised attention to police misconduct. Progressive prosecutors often sided, publicly, with protesters and vowed to press charges against police officers zealously (Holland and Zeidman, 2023). When police officers face stricter legal scrutiny, they might avoid certain activities, thus affecting public safety. There are recorded instances of what is colloquially known as a "blue flu" - a type of strike action undertaken by police officers in which many simultaneously use sick leave - during calls to "defund the police" after the murder of George Floyd and when officers were prosecuted (Grim, 2020; Hansen, 2020). Moreover, police departments facing the threat of heightened legal accountability might choose to influence the elections of progressive prosecutors into office.

Chesa Boudin was elected to the DA's office on November 5, 2019. During Boudin's election campaign, The San Francisco Police Officers Association paid for ads calling Boudin "the #1 choice of criminals and gang members." In December of that year, Boudin's office charged a police officer in the first known excessive-force prosecution in the city's history. Moreover, on June 5, 2020, the DA's office released an official statement announcing "New Appointment and New Policy Designed to Protect the Public From Police Misconduct and Abuse."[3] In the statement, Boudin is quoted saying: "the national movement that has ignited around police abuse has illustrated the importance of having someone who deeply understands how to hold police accountable."

The recall efforts began on January 2, 2021. Richie Greenberg, a former Republican mayoral candidate, started a petition to recall Boudin. In August 2021, this recall attempt fell short due to a failure to achieve the required signatures from city residents. A second, separate campaign to recall Boudin started on April 19, 2021. This time, Mary Jung, former chair of the San Francisco Democratic Party, becomes chair and pitches the campaign as led by Democrats who support criminal justice reform but believe Boudin is ineffective. On November 9, 2021, this recall initiative forced a recall election after 83,000 signatures were gathered. The recall election is set for June 7, 2022. If the recall election results force Boudin out of office, Mayor London Breed would get to choose his successor. Mayor Breed supported Boudin's opponent during the 2019 election

[3] "District Attorney Boudin Announces New Appointment and New Policy Designed to Protect the Public From Police Misconduct and Abuse" the DA's office, Jun. 5, 2020.

for DA. Boudin and Breed later clash after the Mayor declares a "state of emergency" in the high-crime neighborhood of Tenderloin while Boudin maintains that: “We can’t arrest and prosecute our way out of problems that are afflicting the Tenderloin.”

In early 2022, Boudin’s office entered a conflict with the San Francisco Police Department (SFPD), which received broad media coverage. A 2019 agreement between SFPD and the DA’s office made the DA’s Office the lead investigating agency in police use-of-force incidents, police shootings, and in-custody death cases. The agreement was amended and signed by Boudin and the SFPD Chief in 2021. However, in January 2022, the police Chief said he intended to pull out of this memorandum of understanding.[4] The SFPD Chief said that: "trust between the two agencies was irrevocably damaged." [5] At the time, Boudin’s office was prosecuting six officers in five separate use-of-force cases.[6]

Boudin argued that police officers are turning, as an institution, against the prosecutor’s office: "When I was in office, as we got closer to the recall, we had videos that surfaced of police officers in patrol cars, standing by and watching as businesses were being burglarized, making no attempt whatsoever to intervene to arrest suspects." (Holloway, 2023).[7] In the June 7th election, voters split 55% to 45% in support of the recall (the turnout was 46.2% overall).

The recall results were known on the same day of the election. Still, Boudin’s seat became officially vacant 10 days after the San Francisco Board of Supervisors certified the election results at the body’s June 28 meeting. Moreover, despite Boudin’s publicized defeat on June 7th, there was uncertainty about who will take his place and what the future holds for the city’s leading law enforcement elected official: US Commission on Civil Rights Commissioner Michael Yaki told KRON4 there’s a 50-50 chance Boudin could run again in November in a race to fill out the rest of this term.[8] Only a month later, on July 7th, Mayor Breed announced the appointment of Brooke Jenkins to serve as the city’s interim DA. Jenkins was a prosecutor under Boudin but resigned from the San Francisco DA’s Office in October 2021 due to mounting dissatisfaction with the direction of the office (of the Mayor, 2022). SFPD supported her in her bid for the DA’s seat in the following November general election, which she later won.[9]

During the DA recall campaign, San Francisco residents raised the alarm regarding the police ignoring crime and telling residents that they avoid arrests because the DA’s office avoids charges;

[4] Notice from the Chief of Police to DA Boudin, Feb. 2, 2022.

[5] SF Chronicle, Feb. 4, 2022.

[6] SF Chronicle, Feb. 2, 2022.

[7] In Portland, the police chief publicly called city cops to stop telling residents DA Mike Schmidt won’t prosecute crimes (Kavanaugh, 2023).

[8] "Who will replace Chesa Boudin as SF DA?" KRON4, Jul 7, 2022.

[9] "SF District Attorney Brooke Jenkins has cleaned house in one regard, now having dismissed charges in all three police shooting cases brought by her predecessor Chesa Boudin."

in response, the police Chief acknowledged to a reporter that the police has "serious morale issues" due to "intense scrutiny amid the police reform movement and tussles with District Attorney Chesa Boudin."[10] In this paper, we empirically test the claim that the police department changed their behavior in anticipation for San Francisco's DA recall campaign (June 7th, 2022) and DA elections (November 7th, 2022).

4 Data

We combine a variety of data sources to estimate the effect of the recall election of DA Boudin on policing, prosecution, and the resulting jail population in San Francisco. To measure officer-initiated police stops and police incident reports, we use calls for service and police incident reports data from the OpenDataSF portal. These two incident-level data sources allow us to construct detailed measures of daily police activity in each police district and for each type of stop or incident for the time period from January 2018 to November 2022. To measure arrests by SFPD and DA charging behavior, we use an additional arrest-level dataset provided on the OpenDataSF portal by the San Francisco District Attorney's Office showing arrests presented to the district attorney's office and actions taken on each arrest. Finally, we use jail roster data provided by the NYU Public Safety Lab's Jail Data Initiative to measure the total daily jail population, admissions and discharges, and length of jail stays. By using all of these data sources, we can measure any changes in the way both police and prosecutors use their discretion throughout the stages of an encounter: 1) whether police stop and initiate contact with an individual, 2) whether police record a criminal incident when in contact with an individual, 3) whether police arrest in response to a criminal incident and 4) whether the district attorney's office files charges after an arrest has been made.

4.1 Police Stops

The "Law Enforcement Dispatched Calls for Service - Closed Calls" dataset, an SFPD-generated dataset available on the OpenDataSF portal, provides individual call-level data on police calls for service in San Francisco, including "calls [that]originate from the public via calls to the 911 call center or from law enforcement officers in the field upon viewing an incident ('On-View')" (OpenDataSF 2022).[11] We focus on the officer-initiated "on-view" calls, as these are the types of citizen-police interactions that are initiated by officers and in which officers have the most discretion, although we do compare with citizen-initiated 911 calls to ensure that any observed changes

[10] SF Chronicle, Feb. 19, 2022

[11] Data source: https://data.sfgov.org/Public-Safety/Law-Enforcement-Dispatched-Calls-for-Service-Close/2zdj-bwza Dataset explainers: https://datasf.gitbook.io/datasf-dataset-explainers/law-enforcement-dispatched-calls-for-service

in stops do not appear to be police responses to changes in civilian demand for police services.

We use the call type description fields to categorize calls and on-view stops into different crime or non-criminal call types. We exclude from our sample irrelevant or rare call types such as those that appear only in 911 calls and never in on-view stops, administrative call types (e.g., meetings), 311 calls, citizen standby calls, or non-criminal calls in which police assist with obtaining medical or fire department services. We also exclude calls/stops related to protests or riots as our identification strategy relies primarily on abrupt changes over time, and those call types are disproportionately concentrated in the spring and summer of 2020, respectively. We also drop all calls/stops occurring outside of a regular San Francisco police district or that are handled by another agency such as the fired department or EMS.

Table 1 shows the summary statistics of the different categories of stops and calls. During the whole period of our analysis, police contacted, on average, 92 crime-related stops per day, with a little bit less than half of those being for public order offenses. The vast majority of stops are passing calls. "Passing call" is a radio code officers use to log that they are located in a particular place at a specific time, yet they are not performing any further action. It can be used to respond to directives from the chain of command or by the officer at their discretion. Many codes occur at parking lots owned by the transit authority under directed theft abatement.

4.2 Police Incident Reports

Each call for service may or may not result in a police incident report, depending on the events occurring and the responding officers' discretion. Police incident reports are recorded in the "Police Department Incident Reports: 2018 to Present" dataset, also available on OpenDataSF.[12] Officers file the vast majority of incident reports, while non-emergency police reports can be filed online by the public using SFPD's self-service reporting system. We drop from our sample all incidents not occurring in a regular San Francisco police district or not related to criminal activity. Reports are then collapsed on the day the report was filled–not the day the incident occurred.

Table 2 shows the summary statistics of the different categories of incident reports filed both by officers and online by the public.

[12] Data source: https://data.sfgov.org/Public-Safety/Police-Department-Incident-Reports-2018-to-Present/wg3w-h783 Dataset explainer: https://datasf.gitbook.io/datasf-dataset-explainers/sfpd-incident-report-2018-to-present

4.3 Arrests

The next dataset used comes from the San Francisco District Attorney's Office and it is the "District Attorney Actions Taken on Arrests Presented", available on OpenDataSF.[13] The dataset includes information on arrests presented to the SFDA since 2011 and the subsequent actions taken by the District Attorney's Office for each arrest. Therefore, we first explore the number and types of arrests made to study police behavior and discretion, and then we analyze the charging behavior of SFDA. The arrests presented to SFDA are carried out by both the SFPD and other agencies operating in the region.

Table 3 displays the daily average number of arrests made by SFPD and other regional law enforcement departments, and the total number of arrests categorized by different crime types.

Table 4 shows the daily average number of actions SFDA took for each arrest presented by both SFPD and other regional police departments.

4.4 Jail Population

We use data from two different sources to measure changes in the jail population. The first dataset is obtained from the Jail Data Initiative operated by the NYU Public Safety Lab.[14] The data consists of daily detainee-level information compiled from the San Francisco County Jail's roster. It's important to note that the roster provides a daily headcount of the jail population at 5 a.m., so individuals booked and released within less than 24 hours may not be included in the data. To address this limitation, we also utilize a second dataset from the San Francisco Sheriff's Department, which records the number of daily bookings.

Table 5 shows summary statistics from the jail roster and bookings.

5 Empirical Strategy

To estimate the effect of the DA recall election on police actions in San Francisco, we employ an Interrupted Time Series (ITS) estimator with a kink at the recall election date. This methodology allows us to draw inferences by comparing the slopes of each outcome's trend on either side of the election date discontinuity. The primary identifying assumption is that absent a police response to the election, the time trend in the outcome variables would have continued smoothly along the preexisting seasonal trend before and after the election date. If this assumption holds, the difference in the slopes on either side of the election date can be attributed to the effect of the

[13] Data source: https://data.sfgov.org/Public-Safety/District-Attorney-Actions-Taken-on-Arrests-Present/czsm-3ei3

[14] Data source: https://jaildatainitiative.org/ Dashboard: https://publicsafetylab.org/jail-data-initiative

prosecutor's election on police propensity to make a stop, record an incident, or make an arrest or prosecutors' propensity to charge a defendant after an arrest is made. The identification assumption relies on the fact that other than the recall election's results becoming public (The DA admitted defeat the same night), no other change that can affect our outcomes occurred; the DA remained in office for an additional month, during which it was unclear who will replace him or when.

The choice between a kink discontinuity or jump discontinuity estimator in the ITS design depends on the nature of the relationship between the treatment variable and the outcome variable in a given context. In our analysis, the treatment is the recall election event. The event did not force an instant and simultaneous change in officer behavior like a formal policy change would have. The kink design allows for a cumulative effect on stop, incident report, and arrest outcomes due to officers gradually altering their behavior as the election approaches, with the rate of change intensifying or diminishing around a specific point in time. A kink discontinuity estimator is better suited to this setting because the relationship between the election's proximity and police actions is likely to be driven by word-of-mouth communication between officers rather than a top-down directive, resulting in a gradual change in the propensity towards various actions around the election date.

To estimate the effect of the recall election on trends in our various outcomes Y_{wt} - officer-initiated stops, crime incident reports, arrests, DA actions, and jail population - we use the following linear interrupted time series model with a uniform kernel:

$$Y_{wt} = \beta_0 + \beta_1 W_{wt} + \beta_2 After_{wt} + \beta_3 (W_{wt} * After_{wt}) + FirstOfMonth_w + \alpha_d + \varepsilon_{wt} \tag{1}$$

where Y_{wt} represents the count of outcome Y on date t in week w. The running variable W_{wt} is the number of weeks between date t and the DA recall election. For Example, $W_{wt} = 7$ means the observation is from seven weeks past the election date. $After_{wt}$ is a dummy for whether date t is before or after the election date, $FirstOfMonth_w$ is a dummy for whether week w contains the first of the month, and α_d is a day-of-week fixed effect, as crime patterns may vary both throughout the week and around the first of the month (Carr and Packham, 2019). The coefficient β_3 on the interaction between the weekly linear time trend W_{wt} and the election date cutoff dummy $After_{wt}$ is our estimate of the change in the slope of the linear time trend in the jail population induced by the election. We use the same specification to estimate changes in the trend in daily jail bookings.

This regression specification estimates separate linear slopes for the time series trend of the San Francisco jail population for the periods before and after the election and then tests for the difference in slopes at the threshold. We use the same model for the effect of the recall election on placebo outcomes as such as the number of calls made by citizens to the SFPD and the number of citizen-filed online police reports, to ensure that any changes in our main outcomes are not likely to be driven by citizen demand for police intervention.

We use a 10-week bandwidth in our main estimates for all outcomes due to the proximity of the recall election to other relevant events, including the general election in November in which DA Brooke Jenkins was elected to a full term. However, we test the robustness of all estimates to a set of narrower and wider bandwidths to ensure that this modeling choice is not overly influential.

The key identifying assumption underlying the kink ITS design is that, in the absence of the election, the slope of the relationship between the date and the daily number of stops, police-recorded crime incidents, or arrests would have been smooth and continuous. In other words, any observed discontinuity in this relationship at the election threshold can be attributed to the causal effect of the election itself. We also conduct placebo analyses of additional outcomes such as citizen-filed online crime reports (a measure of criminal activity that does not rely primarily on police recording) or 911 calls (a measure of demand for police intervention) to ensure that this change is police driven rather than citizen-driven.

6 Results

Table 6 summarizes our main results. When we compare changes occurring at different discretion points in the life of a criminal incident/case (summarized in Figure 1), we see that the daily counts of SFPD officer-initiated stops, criminal incident reports, and arrests were trending downward during the ten weeks leading up to the recall election, and immediately began increasing after DA Boudin was recalled.

If this increase were driven by underlying criminal activity or citizen demand for police services, we would likely see a corresponding increase in citizen-filed online criminal incident reports or citizen-initiated 911 calls. We find no statistically significant trend break in these outcomes; if anything, we see a noisily estimated decrease in these outcomes, suggesting that the increases in stops, incidents, and arrests were driven primarily by police discretion.

We also explore whether these additional arrests resulted in a change in the DA's propensity to charge an arrest presented by SFPD. There is a statistically significant increase in both the number and proportion of cases dismissed after the recall. Importantly, this increase in case dismissals began on the recall election date and continued after interim DA Jenkins was appointed about four weeks later. While the point estimate suggests a smaller and more noisy estimated increase in the number of cases charged, this increase in dismissed cases appears to be driven entirely by the increase in the number of arrests presented.

Lastly, we find that the increase in stops, resulting incident reports, and resulting arrests culminated in a substantial increase in the average daily San Francisco Jail population, largely driven by an increase in the daily number of bookings by SFPD officers.

Section 6.1 discusses the effect of the recall election on SFPD stops, incident reports, and arrests in more detail, finding overall that increases in police activity were related to non-violent offenses for which police may have a higher degree of discretion in how they respond. Section 6.2 explores DA actions in more detail, showing that the small increases in the number and proportion of cases declined at the time of the recall election are likely to result from changes in the number and composition of arrests presented. Section 6.3 discusses the increase in the jail population that resulted from increased arrests and bookings by the SFPD. Figure 17 shows the robustness of these effects to alternate bandwidths.

6.1 Police Behavior

We begin by exploring three discretion points at which officers choose whether and how to respond to a potential criminal incident. First, officers can either be dispatched to a scene by a resident-initiated 911 call or can choose to conduct an "on-view" stop in which they choose to respond to events they see during their shift. During the time period in our sample, SFPD received an average of about 551 crime-related 911 calls and made about 92 crime-related on-view stops each day. We focus first on on-view stops as officers typically have little discretion in responding to a 911 call and almost total discretion about whether to make an on-view stop.

6.1.1 Officers' Stops vs. Resident Calls

Table 7 shows that in the ten weeks before the recall election, the average number of on-few police stops per day had been decreasing by about 2.5 daily stops (2.8% of the pre-recall mean of about 88 stops per day, reported in Table 1) each week in the 10 weeks before the recall, and began increasing by about 3.6 daily stops (4.1% of the pre-recall mean). The point estimate in column 1 suggests a net slope increase of about 6.1 stops per day (6.9%) beginning on the recall election date. Columns 3-6 of table 7 decompose this effect by the type of crime reported as the initial reason for making the stop. In column 3, we find no statistically significant change in stops for violent offenses. Columns 4-6 show that property, traffic, and public order stops had been decreasing in the 10 weeks prior to the recall election and began increasing in the 10 weeks after the election; this trend reversal resulted in a net slope increase of about 0.7 property-related stops (4.7%), 2.6 traffic-related stops (6.6%), and 2.895 public order-related stops (36%) per day in each week following the recall. Figure 2 visualizes these changes, showing the weekly average of daily on-view stops, overall and for each offense type, with fitted lines showing the time trend in the ten weeks before and after the recall.

The increase in traffic stops is interesting in light of Boudin's stated intent not to prosecute cases centered around contraband found during pretextual traffic stops [LS ADD CITE LATER]; police may have increased traffic stops in anticipation of this policy possibly being reversed when Boudin left office a month later. Additionally, the large relative increase in stops related to public order offenses (sitting/lying on public sidewalks, vandalism, noise, trespassing, dumping, etc.) is consistent with police behavior changing the most in relation to non-urgent matters over which they have the highest level of discretion. Finally, the null finding for violence-related stops is unsurprising. Firstly, because on-view stops for violent offenses are far less common (see summary statistics in Table 1). Secondly, because officers have less discretion in whether to respond to an active violent situation.

Importantly, behavioral responses by police are not the only reason that on-view stops might increase. If underlying criminal activity or civilian demand for police intervention happened to increase around the time of the recall election, police stops could have increased for reasons other than police responses to prosecutor politics. Columns 1-6 of Table 8 present analogous estimates of changes in civilian 911 calls, both overall and by offense type. We find no statistically significant change in calls to police. If anything, there is a noisily estimated decrease in citizen requests for police assistance.

Additionally, Column 7 tests for a change in automated calls made by home alarm systems, a potential (albeit noisy) proxy for burglaries that should be unaffected by either civilian reporting behavior or police behavioral responses to the recall election. Again, we see no statistically significant change and, if anything, a noisy decrease. Weekly averages and estimated slopes are plotted in Figures 3 and 4. Overall, we find no evidence of any underlying changes in criminal activity or citizen demand for police services that would explain the increase in police stops.

6.1.2 *Incident Reports*

Once officers respond to a 911 call or choose to make an on-view stop, the next potential point of discretion is whether they report that a crime has occurred (See Figure 1). During the time period in our sample, SFPD officers recorded about 195 criminal incidents per day on average. Civilians can also file online incident reports, usually related to property or public order offenses, and filed about 74 reports per day within the same 10-week window around the recall.

Table 9 reports estimated changes in the trend in police reports per day at the recall election date, showing a small but statistically significant increase after the recall. In the 10 weeks leading up to the recall, police were recording an average of 188 incidents per day (see Table 2), and this average was relatively stable, decreasing by about 0.5 daily incidents each week (0.3%). This weekly average began increasing by about 1.8 daily incidents for each week after the recall (about 1%), for a total net slope change of 2.3 incidents per day or about 1.2%, as reported in Column 1.

Columns 3-6 again decompose this change by offense type. Consistent with the changes in on-view stops, the slope of the weekly average number of incidents recorded increased by 1.511 daily incidents (1.3%) for property offenses, 0.1626 daily incidents (8.7%) for traffic offenses, and 0.682 daily incidents (27.6%) for drug offenses. These trends before and after the recall are visualized in Figure 6. This pattern is consistent with the changes in on-view stops, and suggests that officers may have reported that some stops were initially made for public order offenses but resulted in a finding of a drug offense during the course of the stop.

We again test for a change in incident reports that cannot be driven by police behavior: those filed online by citizens, usually for theft, property damage, or noise. Table 10 shows no evidence of a statistically significant change in incident reports by San Francisco residents after the recall, and if anything, a small and noisy decrease. However, it should be noted that far fewer reports are filed online by civilians, so very small effects may not be detectable due to limited statistical power.

6.1.3 Arrest Presented to SFDA

After police make a stop or respond to a call, and if they determine that a crime has occurred, their next point of discretion is whether or not to make an arrest (Figure 1) to be presented to the DA for potential prosecution. On average, SFPD made about 18 daily arrests during the relevant time period - about 14 felony arrests and four misdemeanor arrests.

Table 11 estimates the trend break in arrests by SFPD at the recall date. In the ten weeks prior to the recall, SFPD averaged about 17 arrests per day (see Table 3), and the trend in the weekly average was decreasing by about 0.2 arrests (1.1%) each week as the recall approached. In the ten weeks after the recall, the trend reversed, with average daily arrests increasing at a rate of 0.6 average daily arrests (3.3%) in each week after the recall, for a total net slope change of 0.751 average daily arrests (4.4%). Columns 2 and 3 disaggregate by felony and misdemeanor arrests, finding a statistically significant slope increase of 0.813 average daily felony arrests (6.2%) each week. The analogous increase in misdemeanor arrests is not statistically significant. Still, the point estimate would suggest a slope increase of 0.1655 average daily misdemeanor arrests (4.3%) each week, and standard errors are large, so we cannot rule out that the relative magnitude of the change is the same for misdemeanors and felonies. Figure 7 plots these trends in overall, felony, and misdemeanor arrests, all of which were decreasing prior to the recall and began increasing after the recall. For comparison, it also shows trends in the relatively few arrests presented to the San Francisco DA's office by other law enforcement agencies such as the California Highway Patrol and the Bay Area Rapid Transit police. While these arrests are not frequent enough for a formal regression kink estimation to be informative, we see no evidence of a corresponding increase in arrests by these other agencies.

Columns 3-9 of Table 11 disaggregate these arrests by offense type. Unlike the changes in stops an incidents, there is no evidence of a statistically significant trend break in traffic, public order, or drug arrests; however, some traffic or public order offenses may result in citations rather than arrests. There is a marginally significant increase in the slope of the weekly average number of violent (0.3 daily arrests or 4.3%), property (0.4 daily arrests or 16.6%), and "other" (0.2797 daily arrests or 15.7%) arrests per day. Plots of these changes in trends are presented in Figure 8. This pattern of offense types differs from the increases in stops and incident reports, which were concentrated in public order, traffic, drug, and property offenses, suggesting that the relevant margin for some less serious offense types may be whether to make a stop or write a report given a certain observation and the relevant margin for serious or violent offense types may be whether to arrest or not given that a criminal incident has occurred.

6.2 Behavior of Prosecutors

We also examine whether the recall election might have influenced decisions by the District Attorney's office about which arrests to charge and which arrests to dismiss. Note that the recall election occurred on June 7th, and interim DA Brooke Jenkins was not appointed until July 7th, so any changes occurring immediately on the recall date would reflect a change by the Boudin DA's office during the lame-duck period rather than a new DA taking office. Importantly, given our detected changes in the number and possibly composition of arrests presented to the DA's office by the police, we expect corresponding changes in the trends of charges filed and arrests declined for prosecution. For this reason, we test for effects on both the number of arrests prosecuted/dismissed and the proportion of arrests prosecuted.

Table 12 shows that there was little to no change in the rate of charges. We detect an increase in the weekly average number of felony SFPD arrests charged per day (0.3 charges or 4%) in Column 3 of the top panel, as well as an increase in the weekly average of felony arrests dismissed per day (0.3 declinations or 7.7%) in column 5 of the top panel, consistent with the increase in the total number of felony arrests presented (discussed above in section 6.1. We find no statistically significant change in misdemeanor charges and that the average daily number of misdemeanor arrests declined increased, again consistent with increases in arrests. The overall change across felonies and misdemeanors was an increase in both charges and declinations due to more arrests being presented.

The overall proportion of arrests dismissed increased after the recall. Table 4 shows that the proportion of case dismissals out of arrests presented went up by 24% on average (on average, an additional case dismissed per week). It is difficult to assign a mechanism to this change given the uncertainty about the duration of the lame-duck period, the increase in the total number of arrests, and the possible change in the composition of arrests. The DA's office may have been reluctant to take on marginal cases given impending personnel changes, the increase in the total number of arrests may have caused capacity constraints to become binding, or the change in the composition of arrests may have resulted in lower-quality arrests for which there was not sufficient evidence to build cases. Regardless, the increased proportion of arrests dismissed suggests that the increases in the San Francisco jail population discussed below in section 6.3 are unlikely to be driven by changes in the DA's office and more likely driven by increases in arrests and bookings. The bottom panel of Table 12 includes the relatively few arrests presented by agencies other than SFPD, and the results are similar.

Regardless of the underlying causes for the decline in the proportion of cases charged, this phenomenon offers insight into possible influences on police behavior. It could be posited, and it often was, that officers were intentionally moderating their enforcement efforts prior to the recall, perceiving that their arrests might not culminate in charges. They might then logically intensify their efforts once the recall succeeded. Yet, this assumption conflicts with the reality that officers are rarely, if ever, apprised of the prosecutorial fate of their arrests on an individual basis. Contrary to their potential belief, the data show that the rate of arrests resulting in charges actually decreased following the recall. Moreover, the period between the recall election and DA Jenkins's appointment was uncertain, as the election results required certification before any appointment could occur. Given that officers likely operate with incomplete knowledge about the eventual outcomes of their arrests, it remains unclear whether their behavior was a response to a mistaken belief about the changing likelihood of charges or if it represented a strategic reduction in enforcement to potentially impact the election outcome, with a reversion to usual levels of effort once the electoral process concluded.

6.3 Jail Population

Lastly, we examine how each of the changes earlier in the pipeline of a criminal incident led to changes in jail outcomes. Unlike the other discretion points described in Figure 1, this outcome is potentially affected by both police and prosecutor discretion. Table 13 shows that the increases in police activity starting after the June 7th recall election had a significant effect on the local jail population. The rate of change in jail population per day decreased by 11 each week prior to the recall and increased by five after the election (visualized in Figure 10). Further, data on bookings - every person brought to the local jail regardless of whether they stay till the daily head count - confirms the finding that SFPD changed their behavior and decreased the rate of bookings before the election and increased after (see Figure 11). The total slope change in the weekly average daily jail population after the recall suggests a net slope increase of 16 inmates per day each week on average after the recall. While this is only a 2.2% weekly rate of increase compared to the pre-recall mean, by a rough back-of-the-envelope calculation,

$$JailDays = \sum_{w=1}^{10} (16.276 * 7 * w) = 6260.1 \tag{2}$$

The post-recall period witnessed an uptick in policing intensity, leading to approximately 6,260 additional person-days spent in jail over the ten weeks after the recall election. Considering the analyses from earlier sections, it is improbable that this increase stemmed from shifts in crime rates, civilian conduct, or the probability of pre-trial charges and detention. Rather, the San Francisco jail logs indicate a heightened frequency of bookings initiated by SFPD officers.

Concurrently, Figure 14 illustrates a pronounced reduction in the average jail stay duration (till final release) coinciding with a surge in inmate counts. Pre-election, we find a stable flat trend, yet after the recall, the average person in jail is released much faster (from about 270 days till release to less than 50). To quantify the relationship between the burgeoning jail population and the diminished duration of imprisonment, we employed a linear regression model as follows:

$$\text{AverageDays}t = \beta_0 + \beta_1 \text{Population}t + \beta_2 \text{afterRecall} + \beta_3 \text{Population}_t \times \text{afterRecall} + \varepsilon_t \tag{3}$$

Here, AverageDays$t$ denotes the mean jail final stay at time t, Population$t$ represents the inmate count at time t, and afterRecall is a binary indicator which assumes a value of 1 post-June 7 (the recall date), and 0 otherwise. The term Population$_t$ $\times$ afterRecall is the interaction of the inmate count and the post-recall period.

The coefficient for the interaction term, as reported in Table 14, suggests a post-recall reduction in the average jail stay by approximately one and a half days for each additional inmate. This pattern implies a potential shift towards more frequent arrests for minor offenses post-recall, which generally require shorter jail stays. This inference is further supported by Figure 15, which demonstrates an almost perfectly aligned decrease in the share of inmates incarcerated for violent crimes from roughly 35% to a mere 3% after the recall, as depicted in Figure 16 as well. These dynamics suggest that arrests for lower-level offenses subject to higher discretion predominantly drive the post-recall increase in the jail population. Normatively, the declining proportion of inmates held for violent crimes prompts critical discussions about the implications for public safety and the justice system, especially considering the broader impacts of pre-trial detention.

Figures 12 and 13 also show that this trend appears to have reversed when interim DA Jenkins was elected to a full term in the November general election. Formal hypothesis tests surrounding this date are beyond the scope of this paper. Still, these trends present suggestive evidence that criminal justice enforcement in San Francisco continued to be responsive to political events.

6.4 Robustness

While the 10-week bandwidth around the recall is the primary estimate to ensure consistency across outcomes, Figure 17 shows the robustness of the main results to a variety of alternate bandwidths from 5-15 weeks. In general, the main results are not sensitive to the choice of bandwidth. The only exception is 911 calls by citizens; while our main bandwidth of 10 weeks estimates no statistically significant change in trends in citizen demand for police services, some smaller bandwidths produce a statistically significant decrease in calls, and some larger bandwidths produce a statistically significant increase. This is unsurprising, as calls are the highest-frequency outcome, so small changes are estimated more precisely. Our main estimate is not an outlier in either direction.

The smallest bandwidth (5 weeks) may be particularly interesting because most of the post-recall period would constitute weeks when Boudin was still in office. Hence, any impact caused by the transition in the DA's office would not affect these estimates (in this period, the identity or timing of Boudin's replacement was unknown). Results estimated using this bandwidth are similar to the main results but, unsurprisingly, more noisily estimated.

Finally, we conducted a robust placebo test to validate that our results were not confounded by any endogenous factor synchronously occurring with the recall election date. We replicated our analysis using data from the previous year (2021) as a counterfactual scenario, where the recall election had not occurred. Figure 18 and Table 15, display these results. As hypothesized, the trends in police arrests and jail bookings in 2021 were statistically indistinguishable from a flat trend, indicating no underlying seasonal effects that could drive the 2022 outcomes. The decline in police stops at the onset of 2021, which gradually tapered off, suggests a continuing pattern that extends into 2022. This pattern aligns with our theoretical framework, positing a changing dynamic between SFPD and the progressive DA, albeit the magnitude and significance of these trends warrant further investigation to ascertain their contribution to the argument. The summer of 2021 did show some variability in citizen behavior, which, while carefully not attributed to any specific external factors due to a lack of evidence, did not mirror the 2022 data, thereby alleviating concerns regarding potential seasonality effects. This dissimilarity, particularly in directionality, suggests that the changes we observed in 2022 are likely attributable to the recall election rather than seasonal patterns inherent to the data set.

7 Conclusion

Overall, the totality of our results suggests that SFPD increased its effort after the recall of DA Boudin, resulting in increased stops, incident reports, arrests, and person-days in jail in the ten weeks following the recall compared to the ten weeks before, suggesting potentially suppressed police effort leading up to the Boudin recall. It is clear that police responded to the recall election; importantly, this response would be consistent with either the "blue flu" or "wildcat strike" hypothesis that police decrease their effort in response to unfriendly district attorneys or the finding that police tone down some activities in response to potential increases in liability when there is a new - or in this case, "unfriendly" - district attorney (Stashko and Garro, 2023). Regardless, this arbitrary increase in policing resulted in additional days in jail for San Francisco defendants in the ten weeks after the recall compared to the ten weeks before, despite no evidence of increases in criminal activity. It is unclear which level of policing is optimal, but if this difference reflects under-policing before the recall, public safety may have been at risk; if it reflects over-policing after the recall, the post-recall increase resulted in an unnecessary increase in jail detention that is costly both to detainees and to the government. Furthermore, our findings highlight the need to consider the behavioral responses of police when evaluating the effects of progressive prosecutors' policies on crime and public safety.

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8 Tables and Figures

Table 1. Summary Statistics: Stops and Calls, daily level

	Stops (On View)					
	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
All criminal	91.94	24.09	88.18	20.67	95.23	26.47
Violent	5.71	4.00	5.33	3.22	6.05	4.57
Property	15.87	4.98	14.57	5.47	17.00	4.24
Public order	40.98	14.41	39.16	11.67	42.57	16.38
Traffic	29.38	11.19	29.12	10.56	29.61	11.79
Passing call	240.22	59.72	266.35	65.17	217.36	43.54
Alarm	0.23	0.47	0.27	0.49	0.20	0.44
Wellbeing, mental/public health	5.36	2.50	5.82	2.67	4.96	2.30
	911 Calls					
	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
All criminal	550.80	31.85	549.10	34.64	552.29	29.43
Violent	158.46	15.77	154.67	13.95	161.77	16.63
Property	183.38	17.88	183.08	17.87	183.64	18.06
Public order	181.15	18.23	182.51	18.18	179.96	18.35
Traffic	27.81	7.32	28.84	7.48	26.91	7.13
Alarm	62.11	10.70	59.67	10.42	64.25	10.57
Wellbeing, mental/public health	93.65	16.01	102.88	13.34	85.57	13.68
Observations	105		49		56	

Table 2. Summary Statistics: Reports, daily level

	Incident Reports (Not Online)					
	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Incidents Criminal	194.93	30.97	187.94	28.69	201.05	31.83
Violent	35.38	6.96	33.35	5.08	37.16	7.89
Property	118.05	23.28	115.61	23.27	120.18	23.29
Public order	34.75	7.30	34.59	7.85	34.89	6.85
Traffic	1.96	1.30	1.86	1.15	2.05	1.42
Drugs	4.79	4.92	2.53	2.07	6.77	5.79
Total not criminal incidents:	21.04	4.77	21.10	4.90	20.98	4.70
Other non-criminal	16.47	3.89	16.67	4.04	16.29	3.78
Admin	4.46	2.26	4.31	2.46	4.59	2.08
Suicide	0.11	0.40	0.12	0.39	0.11	0.41
	Online Incident Reports					
	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Incidents Criminal	74.26	18.07	67.80	10.63	79.91	21.19
Property	67.59	17.16	61.31	10.15	73.09	20.03
Public order	6.67	2.90	6.49	2.64	6.82	3.13
Observations	105		49		56	

Table 3. Summary Statistics: Arrests, daily level

	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
SFPD						
Total arrests	18.34	5.31	16.92	4.83	19.59	5.44
Total felony	14.30	4.44	13.14	4.15	15.30	4.47
Total misd.	4.05	2.37	3.78	2.22	4.29	2.48
Violent	8.09	3.22	7.18	2.69	8.88	3.45
Property	3.84	2.18	3.76	2.18	3.91	2.18
Traffic	0.11	0.32	0.12	0.33	0.11	0.31
Public order	1.80	1.24	1.67	1.13	1.91	1.32
Drugs	2.11	1.96	2.12	1.89	2.11	2.03
Other	2.14	1.45	1.78	1.37	2.46	1.45
Missing	0.25	0.57	0.29	0.65	0.21	0.49
Not by SFPD						
Total arrests	3.42	2.20	3.94	2.70	2.96	1.53
Total felony	1.70	1.48	2.08	1.73	1.36	1.14
Total misd.	1.72	1.50	1.86	1.78	1.61	1.20
Violent	0.89	1.22	1.02	1.52	0.77	0.87
Property	0.41	0.62	0.51	0.68	0.32	0.54
Traffic	0.03	0.29	0.06	0.43	0.00	0.00
Public order	1.38	1.30	1.59	1.57	1.20	1.00
Drugs	0.18	0.51	0.18	0.44	0.18	0.58
Other	0.43	0.63	0.45	0.61	0.41	0.65
Missing	0.10	0.34	0.12	0.39	0.09	0.29
All agencies						
Total arrests	21.76	5.77	20.86	6.06	22.55	5.45
Total felony	15.99	4.78	15.22	4.83	16.66	4.68
Total misd.	5.77	2.61	5.63	2.88	5.89	2.36
Violent	8.97	3.49	8.20	3.15	9.64	3.66
Property	4.25	2.28	4.27	2.36	4.23	2.22
Traffic	0.14	0.43	0.18	0.53	0.11	0.31
Public order	3.18	1.80	3.27	2.03	3.11	1.59
Drugs	2.30	2.13	2.31	1.94	2.29	2.30
Other	2.57	1.61	2.22	1.52	2.88	1.64
Missing	0.35	0.62	0.41	0.70	0.30	0.54
Observations	105		49		56	

Table 4. Summary Statistics: DA action of arrests, daily level

	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
SFPD						
Charged	10.80	3.81	10.14	3.27	11.38	4.17
Charged felony	9.01	3.40	8.39	3.03	9.55	3.63
Charged misd.	1.79	1.43	1.76	1.44	1.82	1.43
Discharged	5.30	3.29	4.33	2.63	6.14	3.59
Discharged %	0.28	0.14	0.25	0.12	0.31	0.16
Discharged felony	3.99	2.54	3.31	2.00	4.59	2.81
Discharged misd.	1.30	1.48	1.02	1.22	1.55	1.65
Further investigation requested	0.52	0.76	0.53	0.77	0.52	0.76
MTR/Referred to other agency	1.32	1.17	1.41	1.22	1.25	1.13
Other action	0.40	0.63	0.51	0.68	0.30	0.57
Not by SFPD						
Charged	2.30	1.64	2.67	1.93	1.98	1.26
Charged felony	1.13	1.19	1.37	1.42	0.93	0.89
Charged misd.	1.17	1.22	1.31	1.37	1.05	1.07
Discharged	0.74	1.01	0.73	1.17	0.75	0.86
Discharged %	0.21	0.29	0.17	0.26	0.25	0.31
Discharged felony	0.31	0.58	0.29	0.61	0.34	0.55
Discharged misd.	0.43	0.81	0.45	0.94	0.41	0.68
Further investigation requested	0.16	0.40	0.29	0.50	0.05	0.23
MTR/Referred to other agency	0.18	0.39	0.20	0.41	0.16	0.37
Other action	0.03	0.17	0.04	0.20	0.02	0.13
All agencies						
Charged	13.10	4.33	12.82	4.26	13.36	4.40
Charged felony	10.14	3.81	9.76	3.77	10.48	3.85
Charged misd.	2.96	1.80	3.06	1.85	2.88	1.76
Discharged	6.04	3.38	5.06	2.93	6.89	3.54
Discharged %	0.27	0.13	0.24	0.11	0.30	0.13
Discharged felony	4.30	2.62	3.59	2.07	4.93	2.90
Discharged misd.	1.73	1.73	1.47	1.65	1.96	1.78
Further investigation requested	0.69	0.82	0.82	0.88	0.57	0.76
MTR/Referred to other agency	1.50	1.20	1.61	1.24	1.41	1.17
Other action	0.43	0.65	0.55	0.71	0.32	0.58
Observations	105		49		56	

Table 5. Summary Statistics: Jail population and Bookings, daily level

	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Number of inmates	744.48	28.36	732.63	23.30	754.84	28.51
Daily duration	420.77	17.56	430.42	12.67	412.33	16.96
Number of inmates serving:						
less than 24H	8.10	4.07	7.71	4.01	8.43	4.13
more than 24H	736.38	26.78	724.92	21.42	746.41	27.14
less than 48H	17.24	7.06	17.47	8.02	17.04	6.18
more than 48H	727.24	25.49	715.16	18.77	737.80	26.03
less than 72H	27.11	9.14	25.94	10.26	28.14	7.99
more than 72H	717.36	23.69	706.69	17.82	726.70	24.36
Total # of bookings	28.26	5.87	27.69	5.87	28.75	5.88
# of bookings by SFPD	20.73	5.24	19.73	5.00	21.61	5.33
Observations	105		49		56	

Table 6. Overview of Main Results

Outcome	Slope change	Trend pre-election	Trend post-election
Police Behavior			
Police stops			
All Stops (crimes only)	6.082***	-	+
Police reports			
All Incident Reports (crime)	2.33*	-	+
Police arrests (SFPD)			
All arrests	0.751***	-	+
All felony arrests	0.813***	-	+
All misdemeanor arrests	0.1655	-	+
Residents Behavior			
Residents Calls			
Crime related	-0.394	-	-
Non-crime related	-0.612	-	-
Residents Online Reports			
All residents' online reports	-0.433	-	-
DA Behavior			
All charges	0.231	+	+
All dismissals	0.608***	-	+
Charges (felony)	0.3019	-	+
Charges (misdemeanor)	-0.0712	+	+
Dismissals (felony)	0.395***	-	+
Dismissals (misdemeanor)	0.2127*	-	+
Jail Population			
Population	16.276***	-	+
Bookings (all)	1.068***	-	+
Bookings (SFPD)	0.991***	-	+

Note: All analyses utilize the rdrobust function to estimate the change in slope of the outcome concerning the weeks around the recall event. The specification spans a 10-week bandwidth before and after the recall. In essence, the estimate captures the difference in outcome trends before and after the recall over a 10-week period. All estimates rely on full police data: SFPD and other agencies.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Police Stops

	(1) Crimes	(2) Passing calls	(3) Violent	(4) Property	(5) Traffic	(6) Public order
Conventional	6.082***	2.80	−0.0644	0.686**	2.566***	2.895***
	(0.948)	(2.16)	(0.1665)	(0.233)	(0.535)	(0.476)
slope.left	-2.46	-2.24	-0.07	-0.3	-0.98	-1.11
slope.right	3.62	0.56	-0.13	0.38	1.58	1.79
nobs.left	519	519	519	519	519	519
nobs.right	270	270	270	270	270	270
nobs.effective.left	70	70	70	70	70	70
nobs.effective.right	77	77	77	77	77	77

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. Police Calls

	(1) Crimes	(2) Mental/public health	(3) Violent	(4) Property	(5) Traffic	(6) Public order	(7) Alarm
Conventional	−0.394	−0.612	−0.915	0.901	−0.093	−0.287	−0.364
	(1.407)	(0.690)	(0.693)	(0.846)	(0.335)	(0.838)	(0.472)
slope.left	-0.86	-0.78	-0.21	-0.77	0.13	-0.02	0.16
slope.right	-1.26	-1.39	-1.12	0.13	0.04	-0.31	-0.2
nobs.left	519	519	519	519	519	519	519
nobs.right	270	270	270	270	270	270	270
nobs.effective.left	70	70	70	70	70	70	70
nobs.effective.right	77	77	77	77	77	77	77

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9. Police Incident Reports

	(1) Crimes	(2) Not crime	(3) Violent	(4) Property	(5) Traffic	(6) Public order	(7) Drugs
Conventional	2.33*	0.170	−0.0408	1.511*	0.1626*	0.0181	0.682***
	(0.91)	(0.230)	(0.3142)	(0.709)	(0.0816)	(0.3268)	(0.148)
slope.left	-0.52	0.01	0.02	-0.71	-0.02	0.06	0.13
slope.right	1.81	0.18	-0.02	0.8	0.15	0.08	0.81
nobs.left	1615	1615	1615	1615	1615	1615	1615
nobs.right	268	268	268	268	268	268	268
nobs.effective.left	70	70	70	70	70	70	70
nobs.effective.right	77	77	77	77	77	77	77

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. Citizen Incident Reports (Online)

	(1) All incident reports	(2) Property	(3) Public order
Conventional	−0.433	−0.335	−0.0975
	(0.637)	(0.595)	(0.1909)
slope.left	-0.06	0.02	-0.08
slope.right	-0.49	-0.32	-0.18
nobs.left	1615	1615	1615
nobs.right	268	268	268
nobs.effective.left	70	70	70
nobs.effective.right	77	77	77

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11. Arrests

	(1) All	(2) Felony	(3) Misdemeanor	(4) Violent	(5) Property	(6) Traffic	(7) Public order	(8) Drugs	(9) Other
SFPD									
Conventional	0.751***	0.813***	0.1655	0.30813+	0.361***	-0.000698	0.0277	0.0544	0.2797**
	(0.216)	(0.207)	(0.1244)	(0.16021)	(0.108)	(0.019179)	(0.0646)	(0.0884)	(0.0895)
slope.left	-0.19	-0.24	-0.02	-0.09	-0.22	-0.01	-0.01	0.14	-0.09
slope.right	0.56	0.57	0.14	0.21	0.14	-0.01	0.02	0.2	0.19
All law enforcement									
Conventional	0.723**	0.787***	0.168	0.230	0.384***	0.00797	0.0439	0.0566	0.2945***
	(0.252)	(0.221)	(0.146)	(0.180)	(0.111)	(0.02006)	(0.0997)	(0.0900)	(0.0881)
slope.left	-0.15	-0.19	-0.02	-0.01	-0.23	-0.02	-0.04	0.15	-0.05
slope.right	0.58	0.6	0.15	0.22	0.15	-0.01	0.01	0.21	0.24
nobs.left	519	519	519	519	519	519	519	519	519
nobs.right	265	265	265	265	265	265	265	265	265
nobs.effective.left	70	70	70	70	70	70	70	70	70
nobs.effective.right	77	77	77	77	77	77	77	77	77

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12. DA action of arrests presented

	(1) All charges	(2) All Declinations	(3) Felony Charges	(4) Misdemeanor Charges	(5) Felony declinations	(6) Misdemeanor declinations	(7) Further investigation	(8) Refer to other agency	(9) % Declinatio of arrests
SFPD arrests									
Conventional	0.3039+	0.529***	0.3390*	-0.0351	0.335**	0.1943**	0.0298	0.0871	0.02174**
	(0.1808)	(0.138)	(0.1543)	(0.0834)	(0.116)	(0.0734)	(0.0442)	(0.0595)	(0.00771)
slope.left	0	-0.24	-0.08	0.08	-0.13	-0.11	0	0.01	-0.01
slope.right	0.3	0.29	0.26	0.04	0.21	0.09	0.03	0.09	0.01
nobs.left	519	519	519	519	519	519	519	519	519
nobs.right	265	265	265	265	265	265	265	265	265
nobs.effective.left	70	70	70	70	70	70	70	70	70
nobs.effective.right	77	77	77	77	77	77	77	77	77
All arrests									
Conventional	0.231	0.608***	0.3019+	-0.0712	0.395***	0.2127*	0.00362	0.0810	
	(0.209)	(0.149)	(0.1745)	(0.0955)	(0.119)	(0.0877)	(0.04665)	(0.0617)	
slope.left	0.05	-0.26	-0.04	0.09	-0.16	-0.1	0.03	0.01	
slope.right	0.28	0.35	0.27	0.01	0.23	0.11	0.03	0.09	
nobs.left	519	519	519	519	519	519	519	519	
nobs.right	265	265	265	265	265	265	265	265	
nobs.effective.left	70	70	70	70	70	70	70	70	
nobs.effective.right	77	77	77	77	77	77	77	77	

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13. Jail Outcomes

	Population	Bookings (all)	Bookings (SFPD)
Conventional	16.276***	1.068***	0.991***
	(0.358)	(0.233)	(0.208)
slope.left	-9.84	-0.25	-0.24
slope.right	6.44	0.82	0.75
nobs.left	146	154	518
nobs.right	203	210	210
nobs.effective.left	62	70	70
nobs.effective.right	73	77	77

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14. Regression results of average jail stay duration (days) on jail population and after June 7 recall election.

Coefficient	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	166.72	42.28	3.94	<0.001
Population	0.16	0.05	3.03	0.002
After Recall	1029.37	65.89	15.622	<0.001
Population x After Recall	−1.50	0.08	−17.67	<0.001

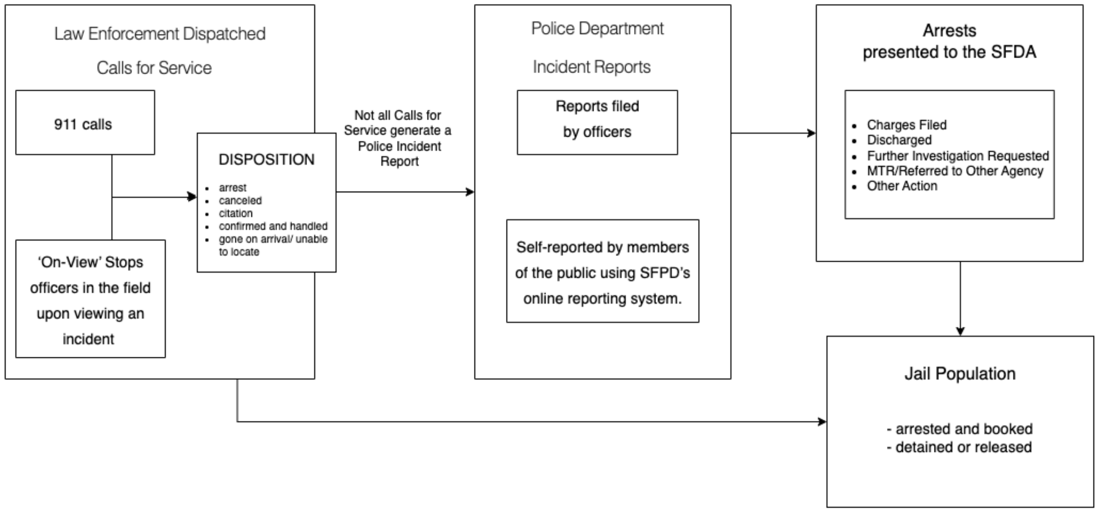
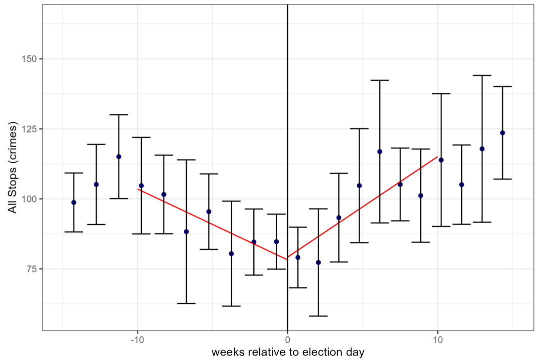
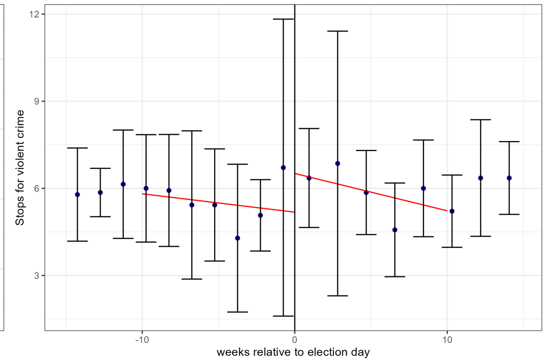


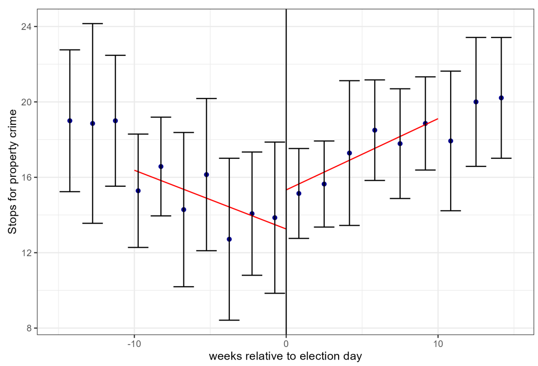
Figure 1. Discretion Points at Each Stage of a Criminal Incident



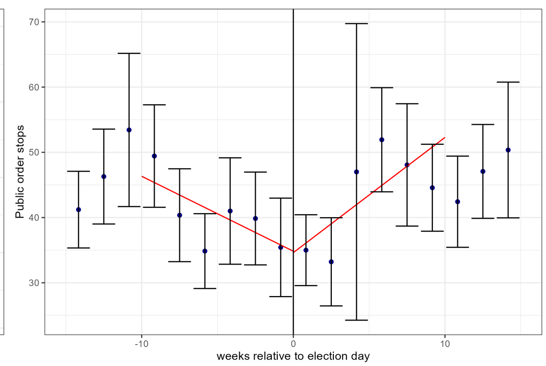
(a) All crime related stops



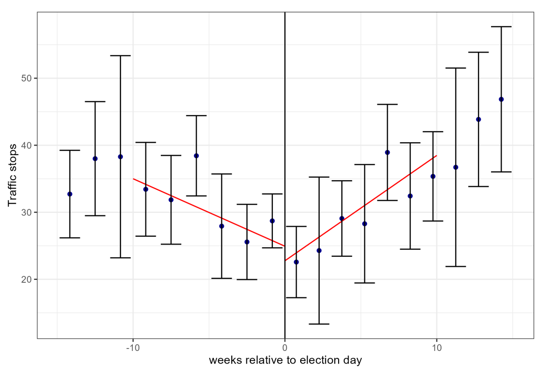
(b) Violent



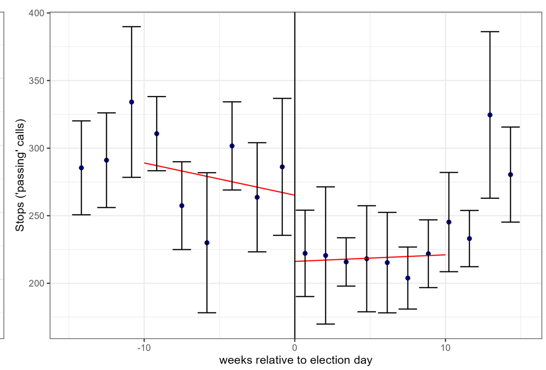
(c) Property



(d) Public order



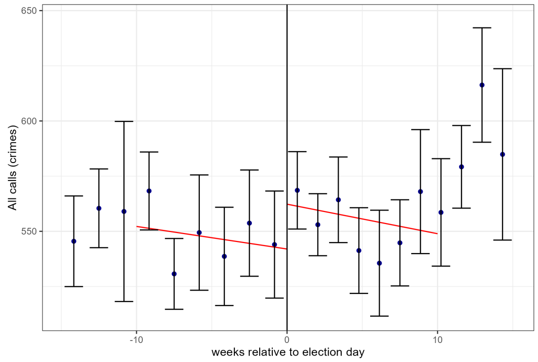
(e) Traffic



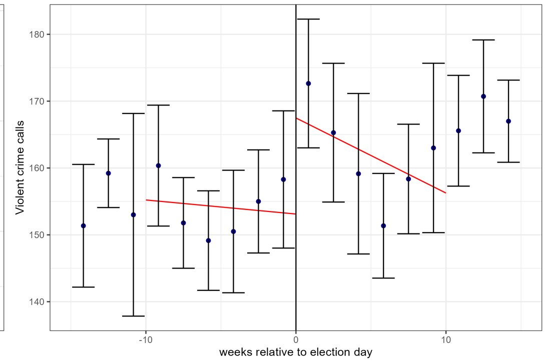
(f) Passing-calls

Figure 2. Officers' Stops, weekly 2022

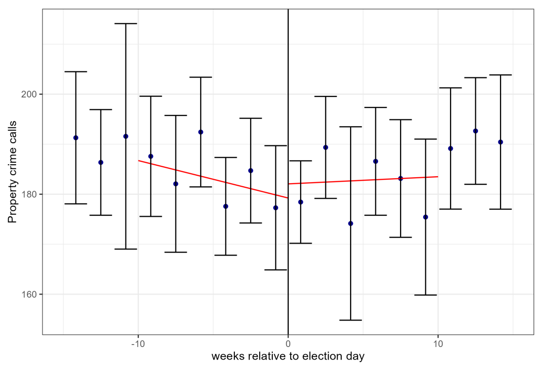
Note: Daily police stops data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.



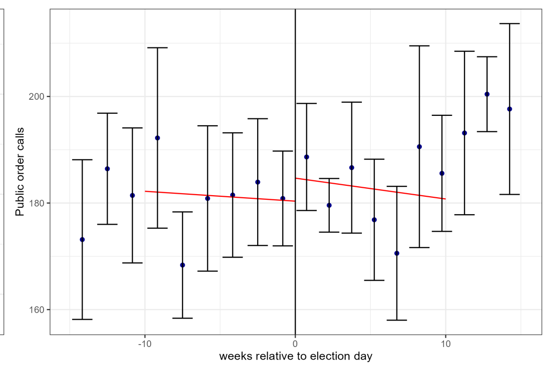
(a) All crime related calls



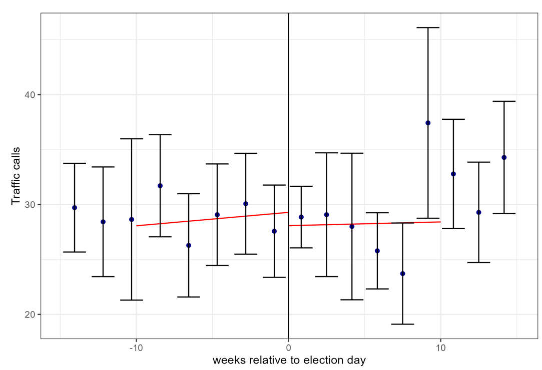
(b) Violent



(c) Property



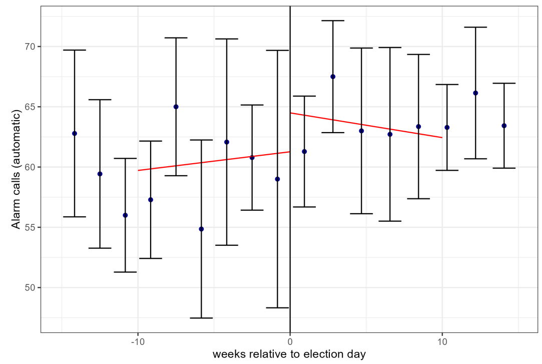
(d) Public order



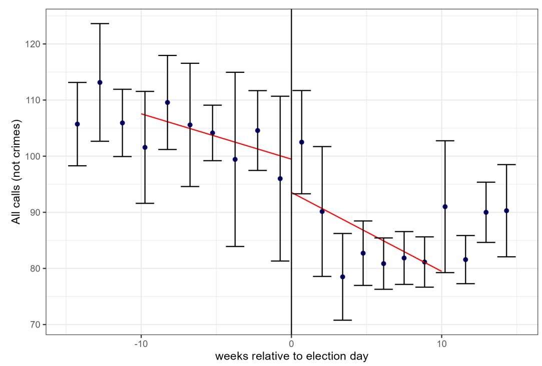
(e) Traffic

Figure 3. 911 Calls, weekly 2022

Note: Daily police calls data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.



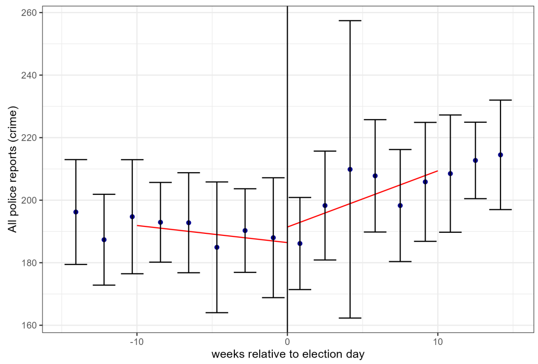
(a) Alarm



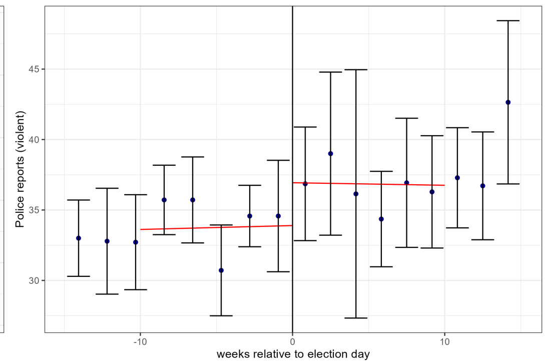
(b) Wellbeing, mental/public health

Figure 4. 911 Calls (placebo), monthly 2022

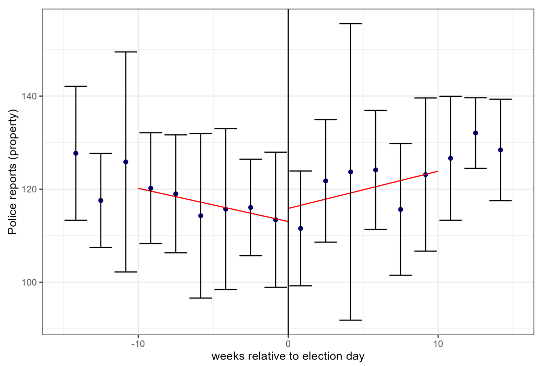
Note: Daily police calls data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.



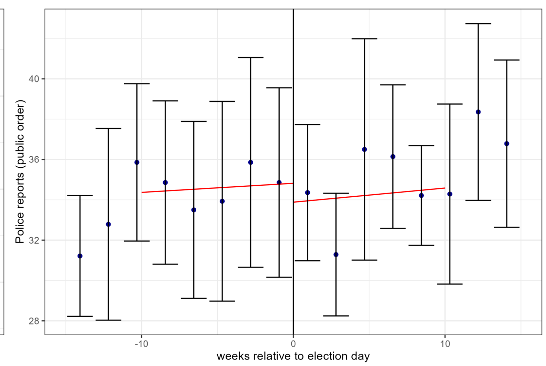
(a) All crime reports by officers



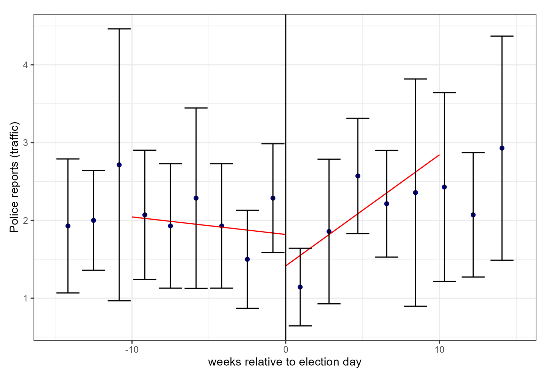
(b) Violent



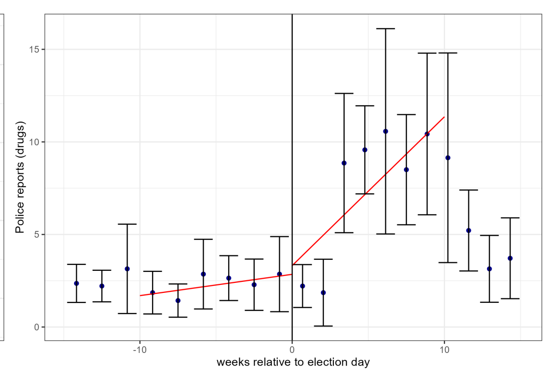
(c) Property



(d) Public order

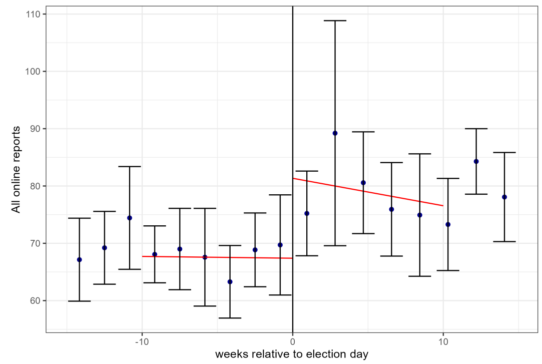


(e) Traffic

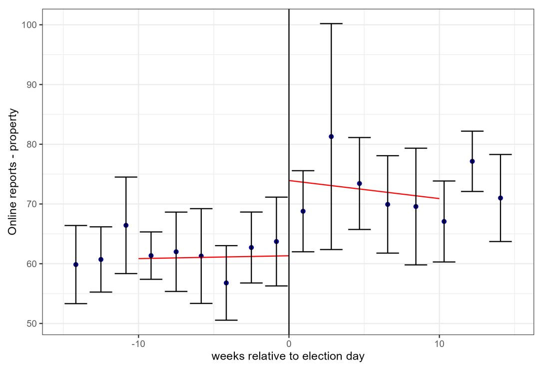


(f) Drug

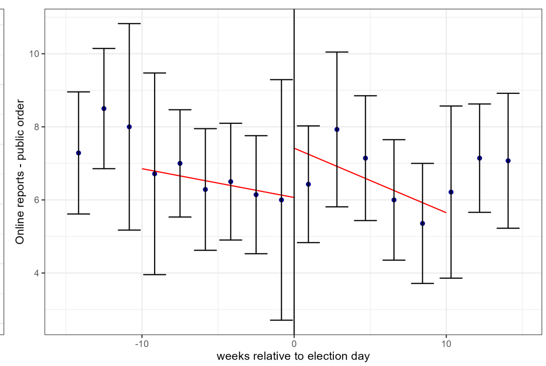
Figure 5. Reports filled by officers, weekly 2022
Note: Daily police reports data, 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin. Two local regression models are estimated using a bandwidth of 10 weeks to construct the fits.



(a) All crime reports filled online

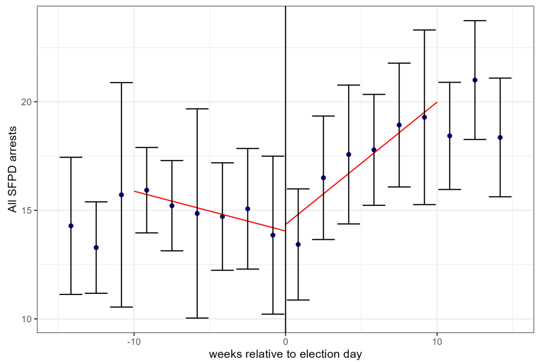


(b) Property

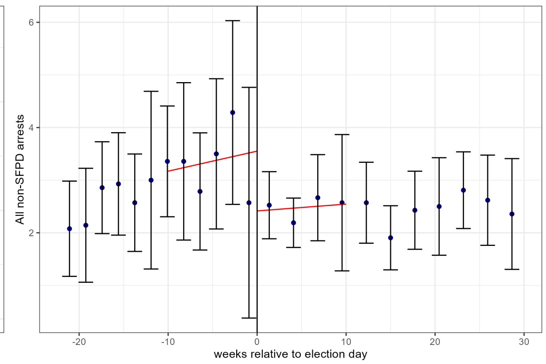


(c) Public order

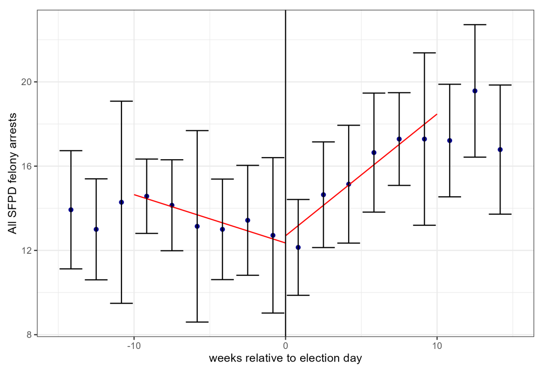
Figure 6. Reports filled online, weekly 2022
Note: Daily citizen reports data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.



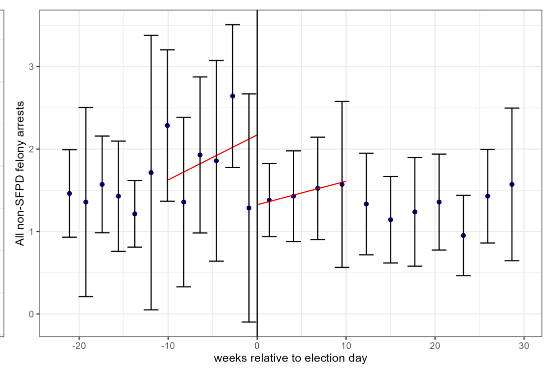
(a) Arrests of SFPD



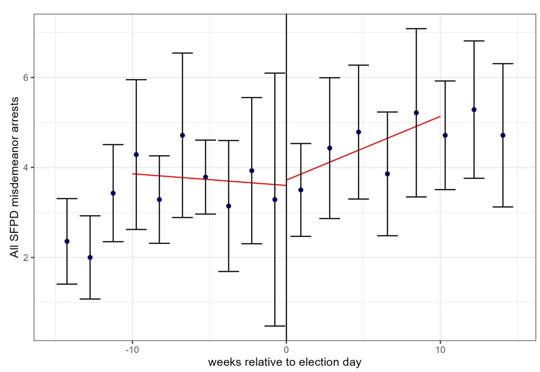
(b) Arrests by not SFPD



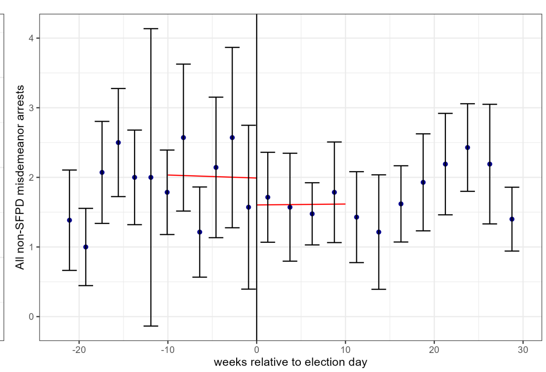
(c) Felony arrests of SFPD



(d) Felony arrests by not SFPD

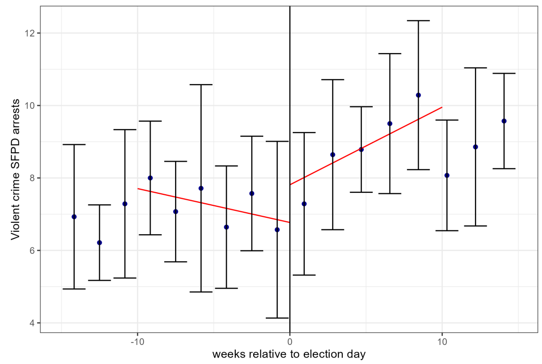


(e) Misdemeanor arrests of SFPD

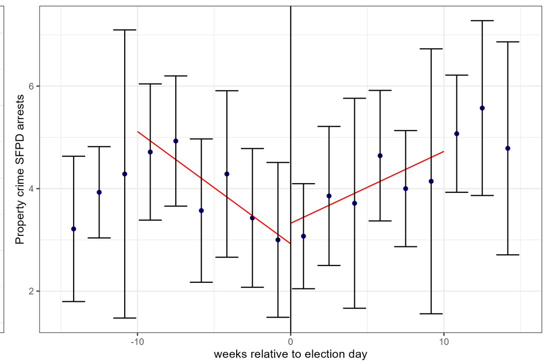


(f) Misdemeanor arrests by not SFPD

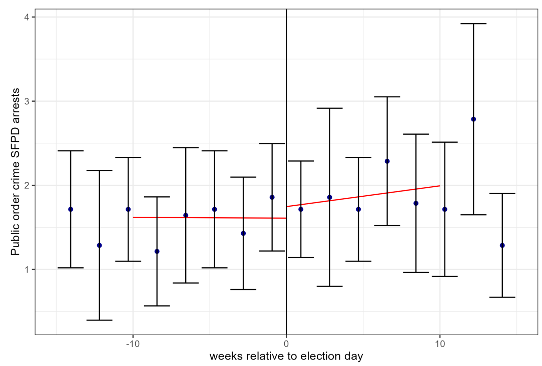
Figure 7. Arrests, weekly 2022
Note: Daily police arrests data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.



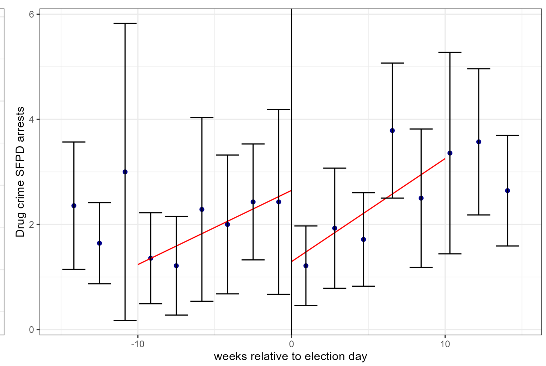
(a) Violent



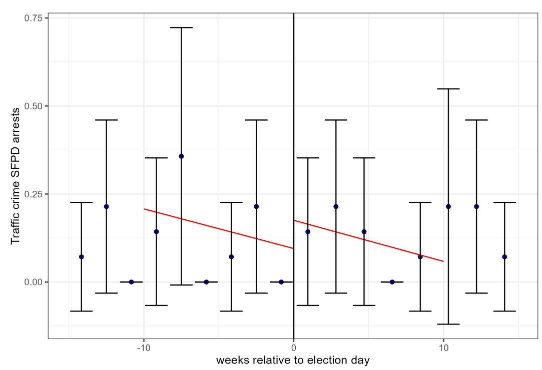
(b) Property



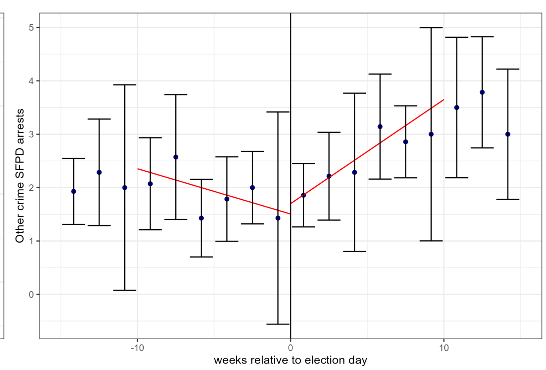
(c) Public order



(d) Drug

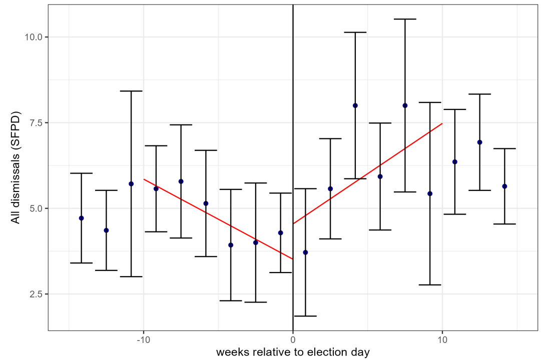


(e) Traffic

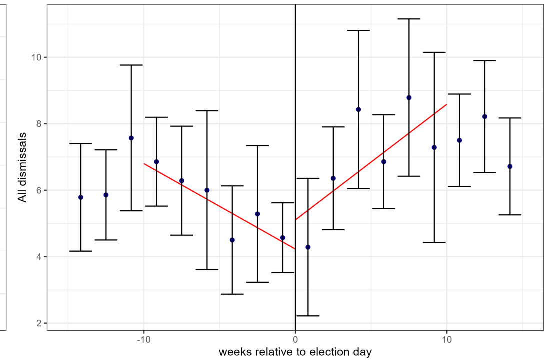


(f) Other

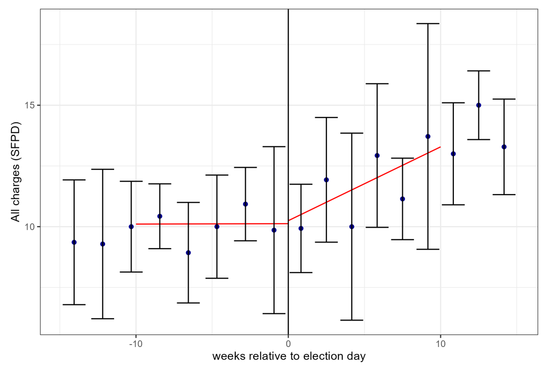
Figure 8. Arrests of SFPD by types of crimes, weekly 2022
Note: Daily SFPD arrest data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.



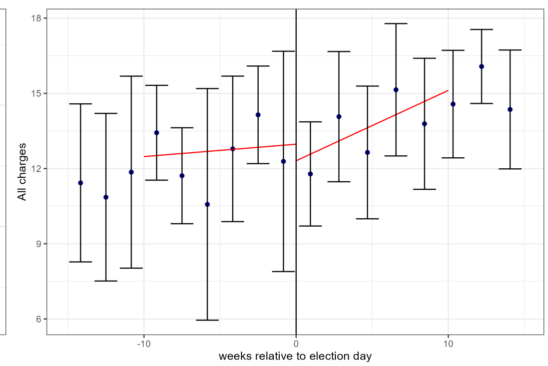
(a) Num of dismissals of SFPD arrests



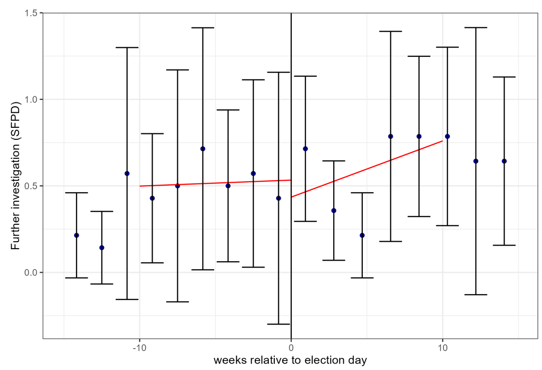
(b) Num of dismissals of all arrests



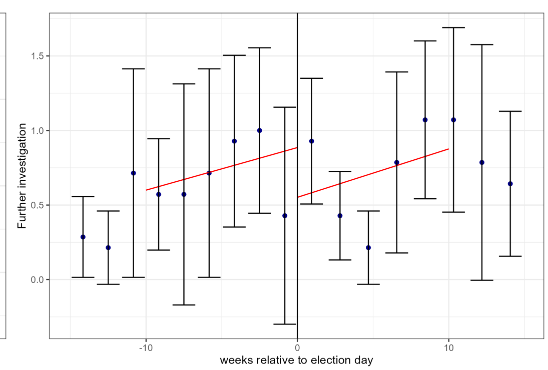
(c) Num of charges of SFPD arrests



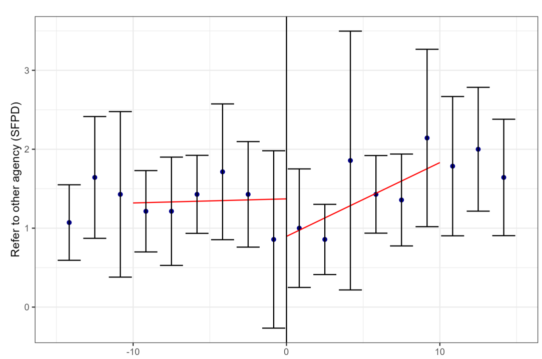
(d) Num of charges of all arrests



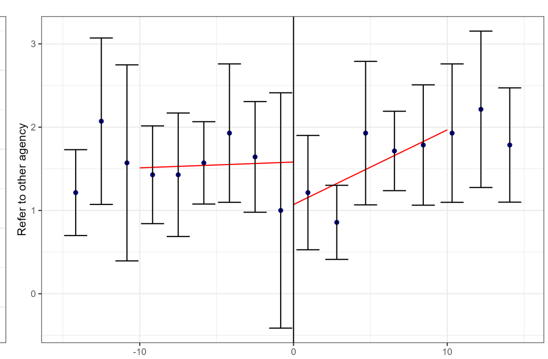
(e) Num of further investigation requested of SFPD arrests



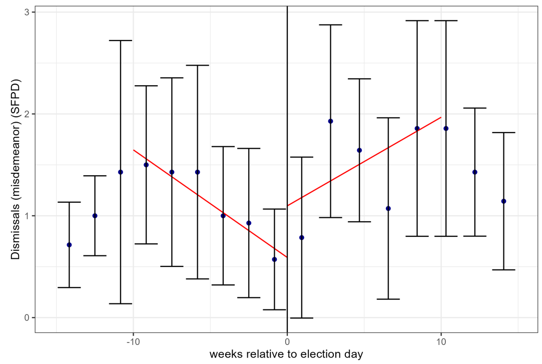
(f) Num of further investigation requested of all arrests



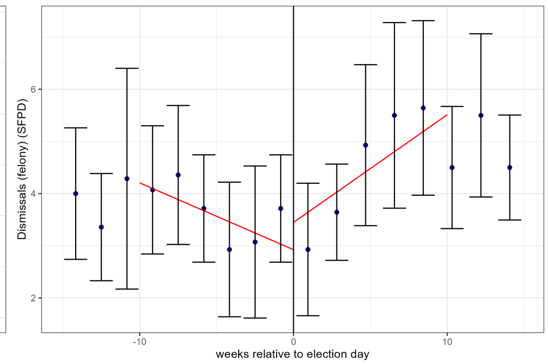
(g) Num of MTR/Referred to other agency of SFPD arrests



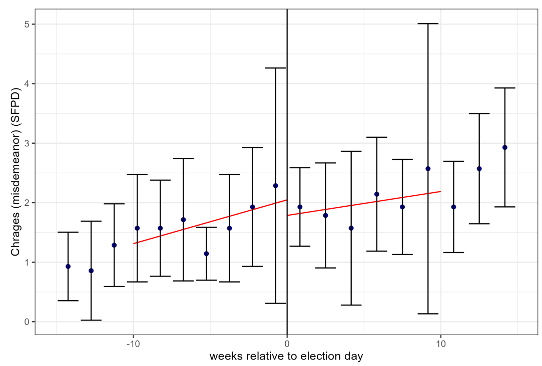
(h) Num of MTR/Referred to other agency of all arrests



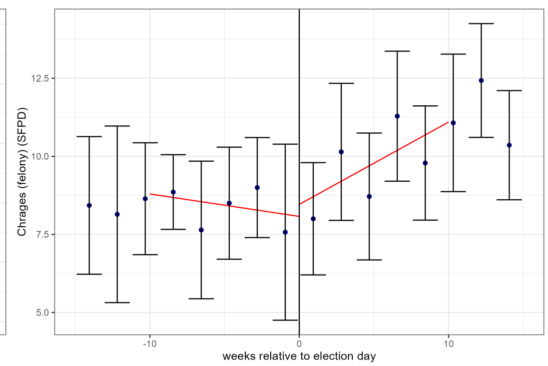
(i) Dismissals of misdemeanor SFPD arrests



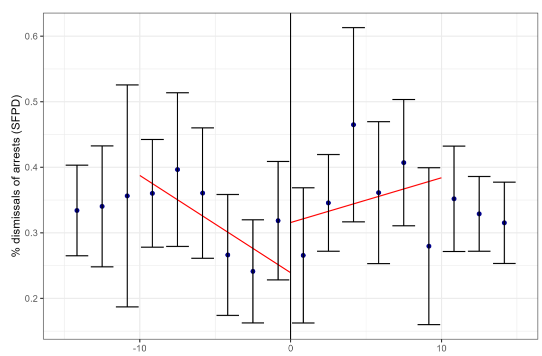
(j) Dismissals of felony SFPD arrests



(k) Charges of misdemeanor SFPD arrests



(l) Charges of felony SFPD arrests



(m) % dismissals of SFPD arrests

Figure 9. DA actions of arrests, weekly 2022

Note: Daily DA action on arrests presented data from 2022. The vertical line marks the recall election date (June 7th). Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day) to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.

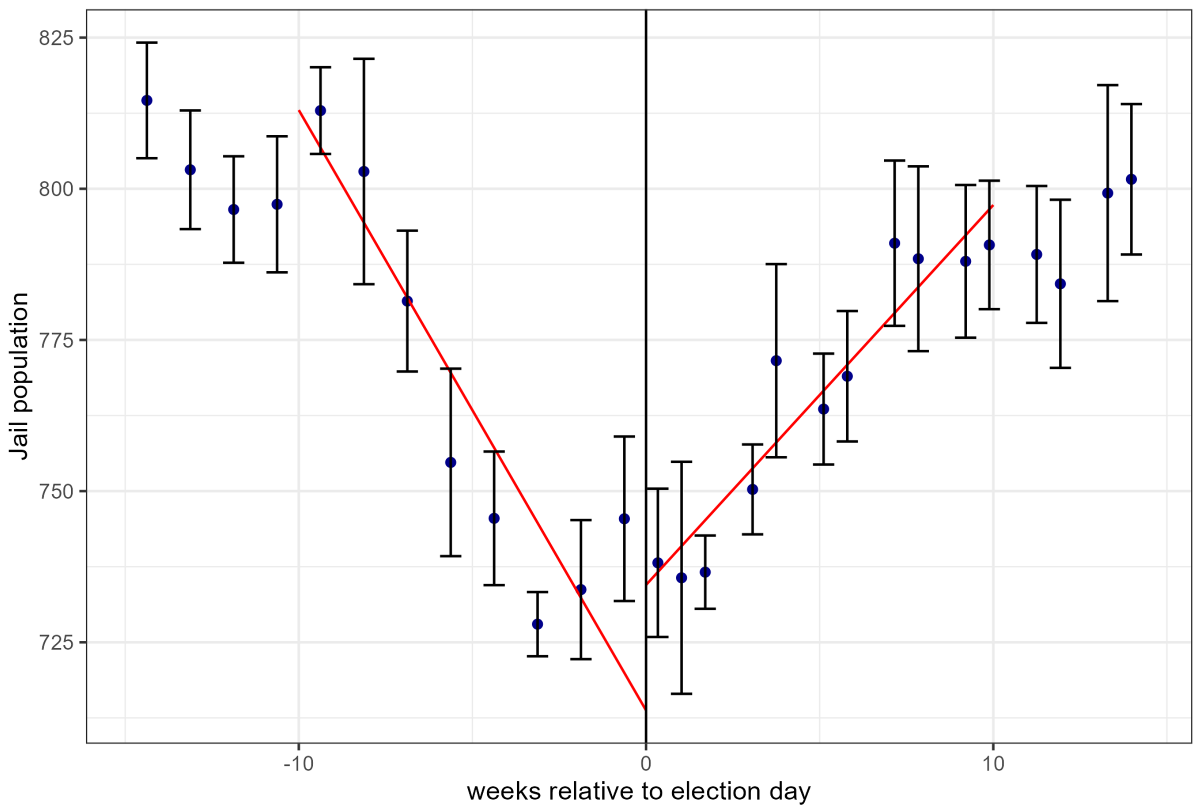


Figure 10. Daily jail population
Note: Daily jail population data from December 24th, 2021, until Decemebr 28th, 2022. The vertical line marks the recall election date (June 7th). This figure was generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable (weeks relative to election day), to minimize the variance of the estimated treatment effect. Within each bin, the mean jail population and its standard error are calculated, with the latter used to generate 95% confidence intervals represented by the error bars in the plot. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.

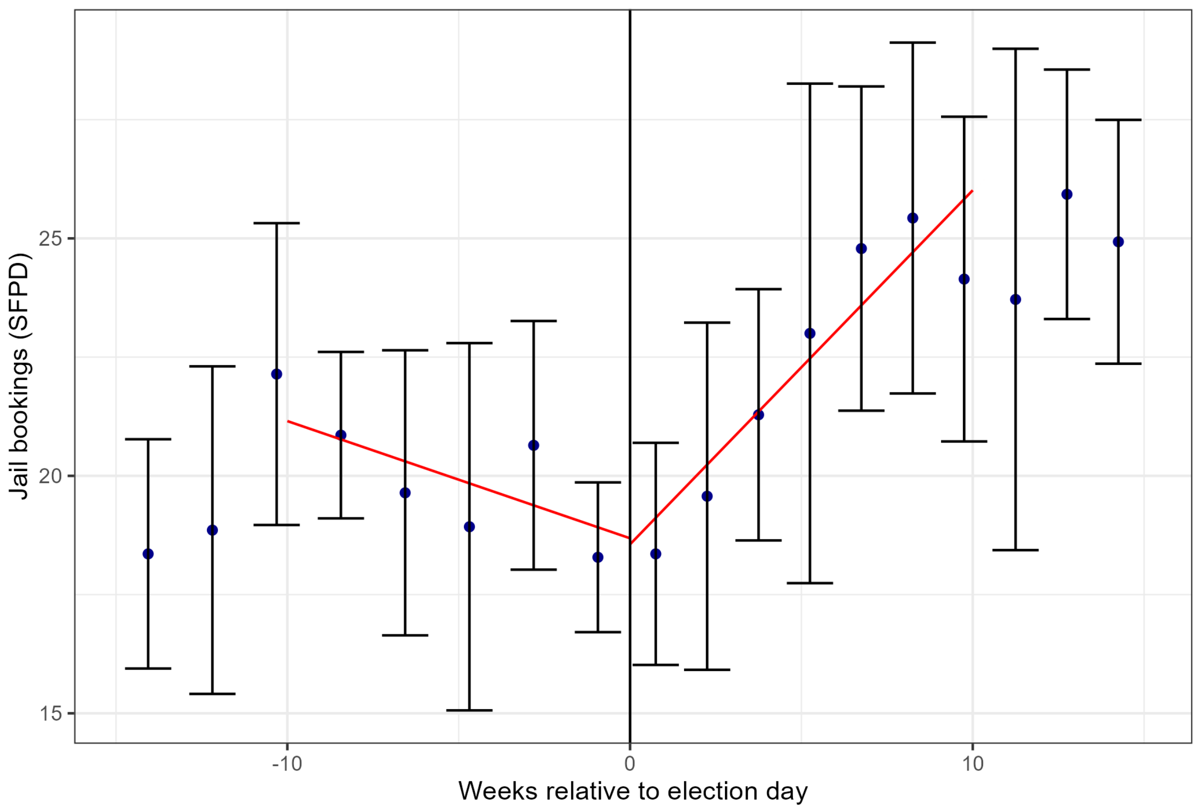


Figure 11. Jail bookings from SFPD
Note: This figure presents a regression discontinuity plot of weekly jail bookings in San Francisco by weeks relative to the recall election day. The analysis uses the rdrobust package in R with a polynomial order of 1. The plot is divided into bins of the running variable as determined by an evenly-spaced method that mimics variance ("esmv"), the default method used by the rdrobust package. Each point on the plot represents the average number of jail bookings within a bin. The error bars represent the 95% confidence interval around each bin's mean. The solid lines on either side of the discontinuity represent local polynomial fits, which are used to model the relationship between the running variable and the outcome variable within the specified bandwidth of 10 weeks in both directions.

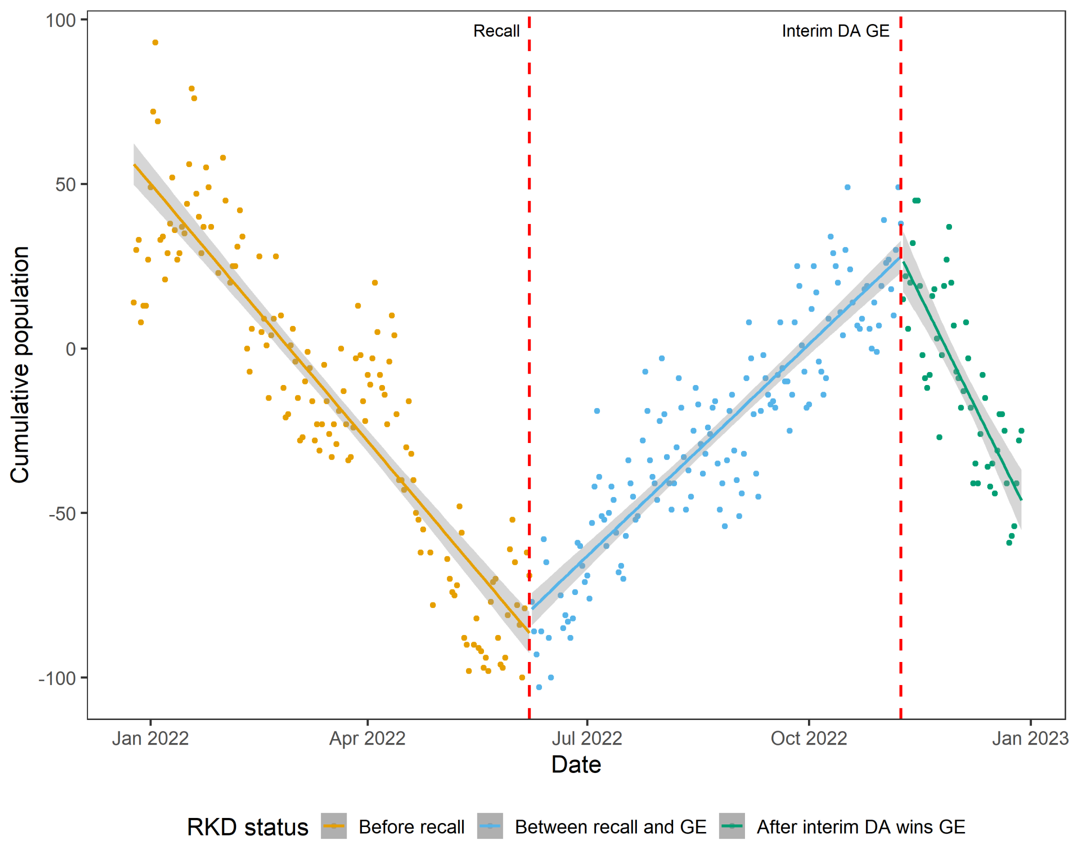


Figure 12. Cumulative jail population
Note: Cumulative daily jail population data from December 24th, 2021, until Decemebr 28th, 2022. The vertical lines mark the recall election date (June 7th) and the general election (November 8th). The regression lines are the first polynomial with 95% confidence intervals.

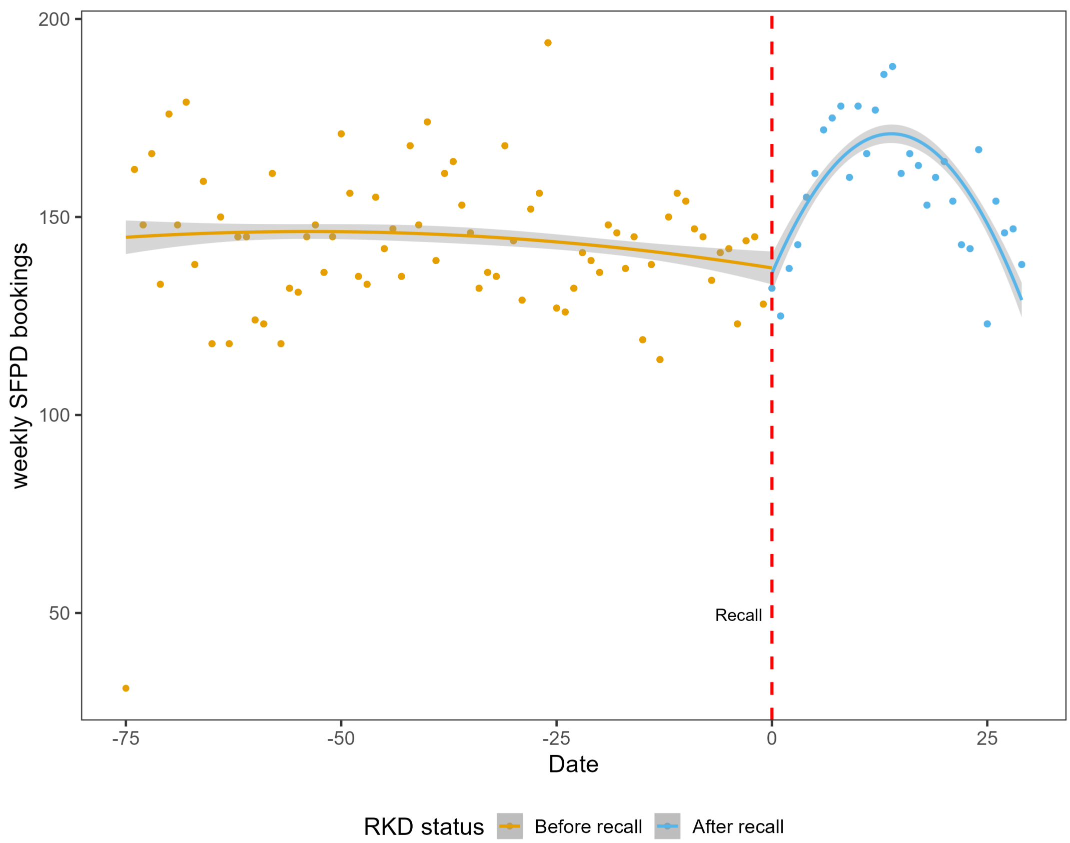


Figure 13. Jail bookings from SFPD
Note: This figure shows the total bookings made by SFPD by week relative to the recall election week (x = 0). The regression lines show the second polynomial relationship between the weekly bookings and the week of the recall election with 95% confidence intervals.

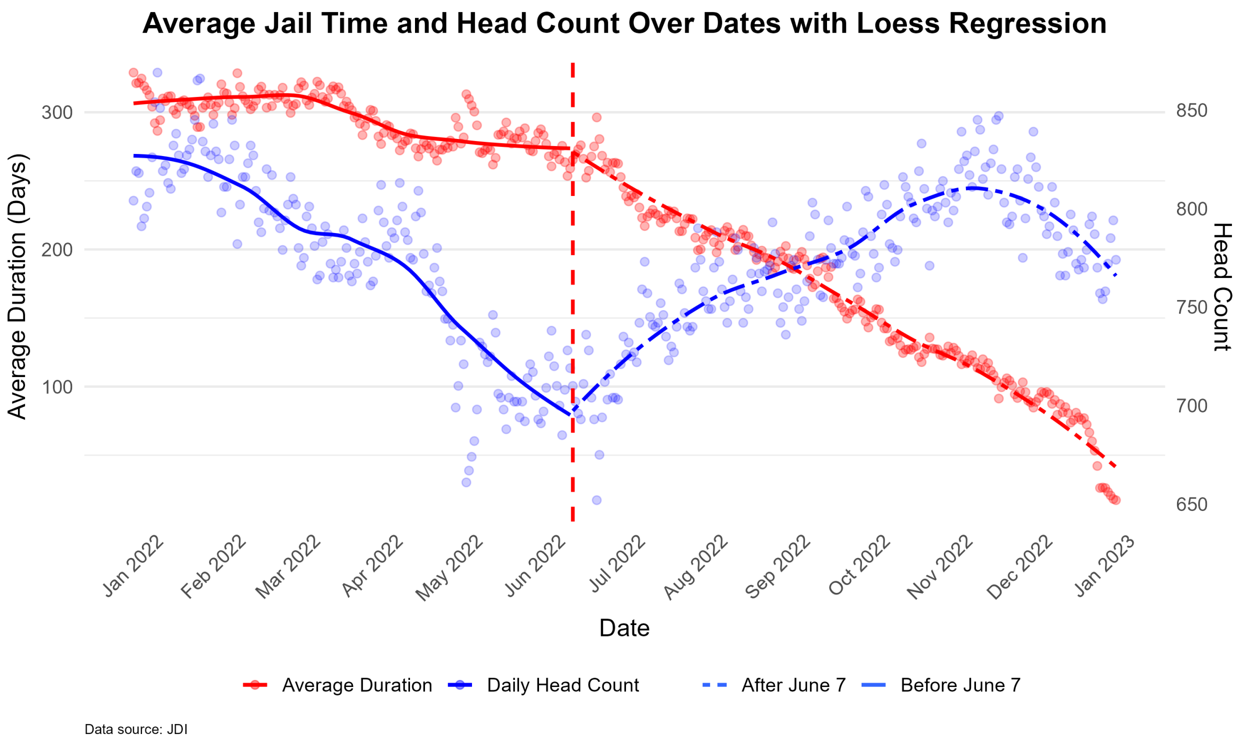


Figure 14. Average Jail Stay Duration
Note: This figure shows in red the average duration, till release, in days of all the people in San Francisco jail on a given day with a Loess-fitted line. In blue, the figure shows the jail population.

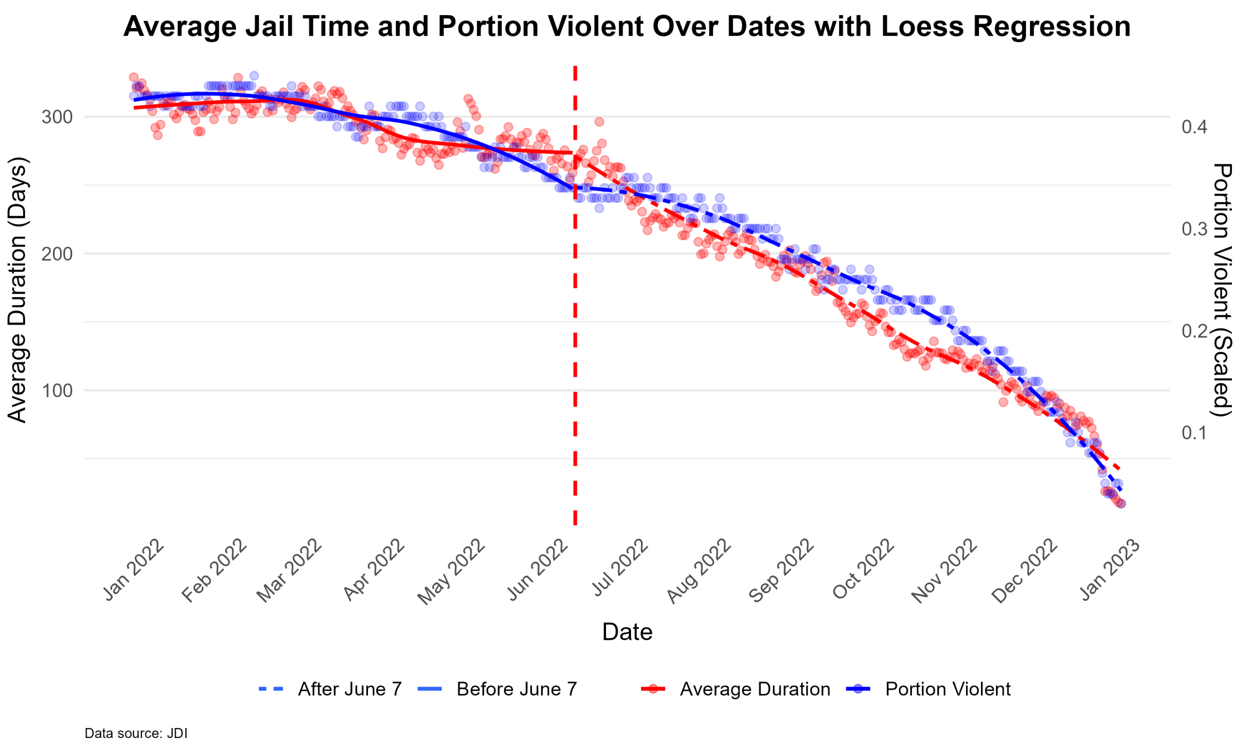


Figure 15. Average Jail Stay Duration
Note: This figure shows in red the average duration, till release, in days of all the people in San Francisco jail on a given day with a Loess-fitted line. In blue, the figure shows the proportion of people held in jail with a top offense "violent."

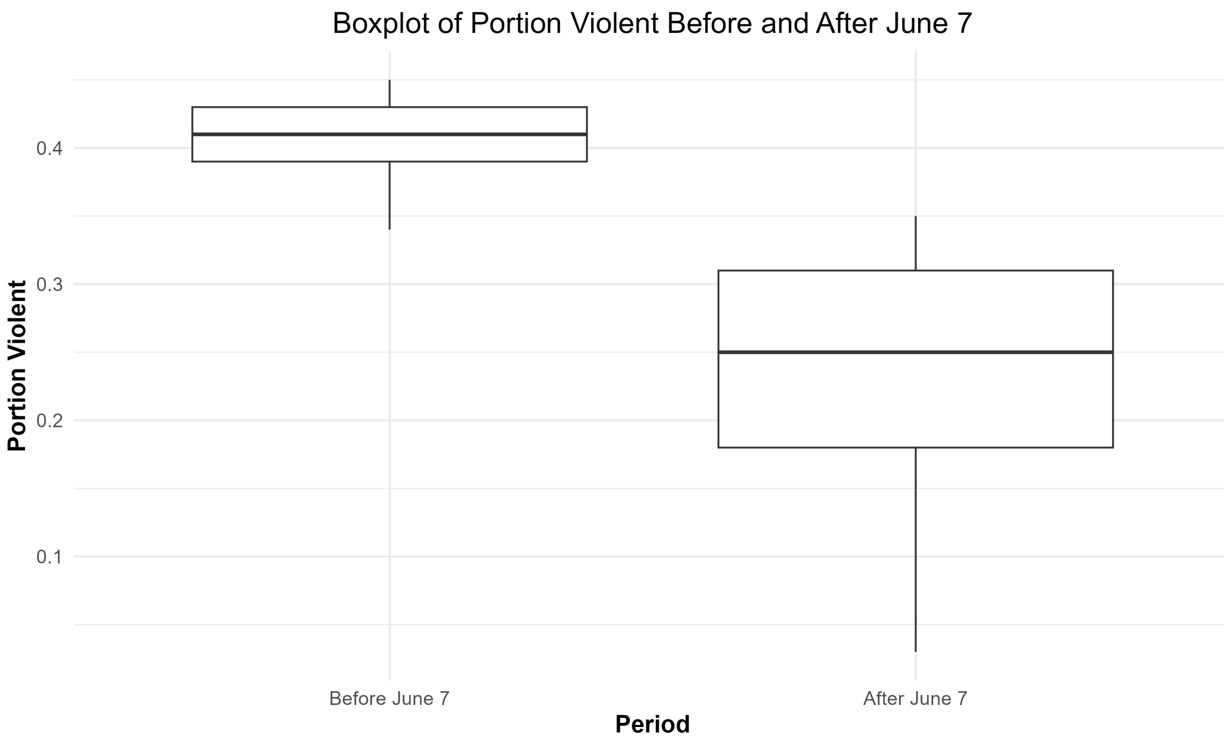
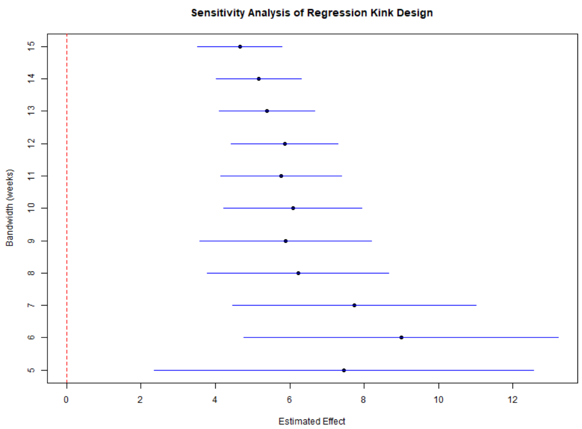


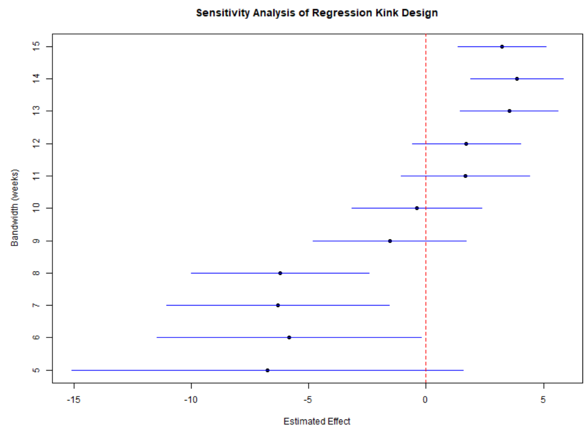
Figure 16. Average Jail Stay Duration
Note: This figure shows boxplots of the proportion of people held in jail with a top offense "violent."

9 APPENDIX

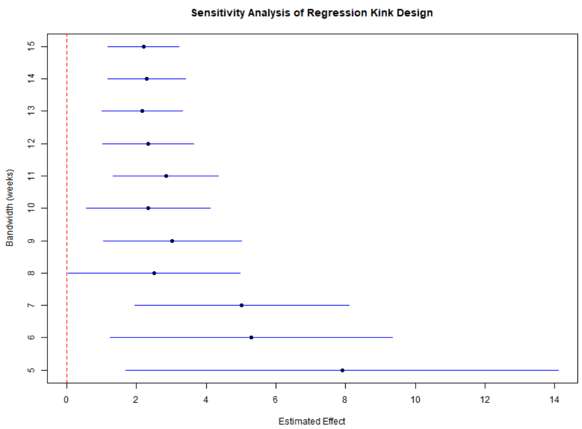
9.1 BW Sensitivity



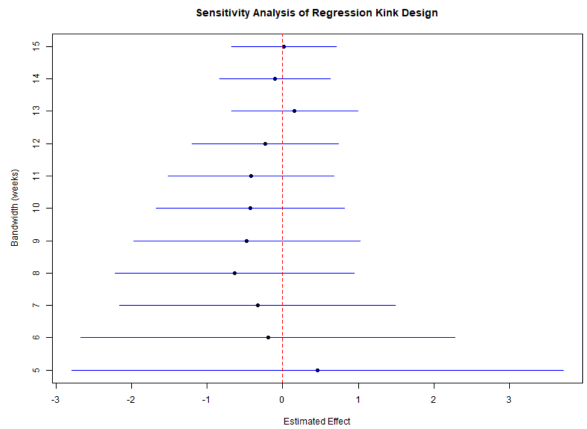
(a) All stops



(b) All calls

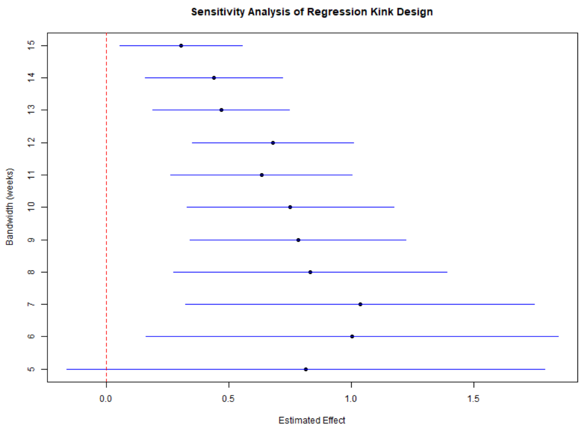


(c) Police report incidents

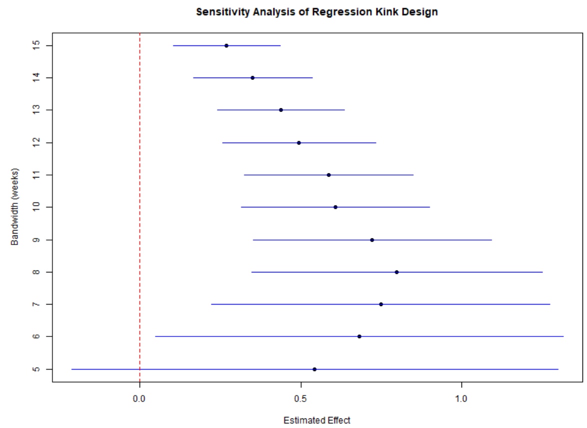


(d) Online incident reports

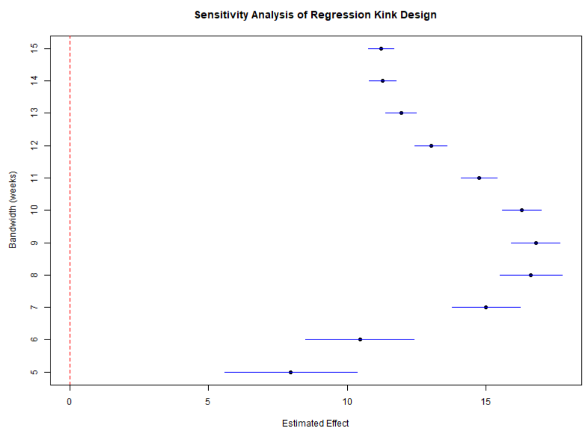
Figure 17. BW sensitivity analysis, Part 1



(e) All arrests of SFPD



(f) SFDA total dismissals



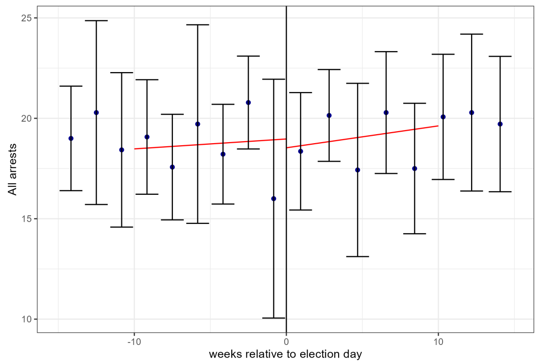
(g) Jail population

Figure 17. BW sensitivity analysis, Part 2

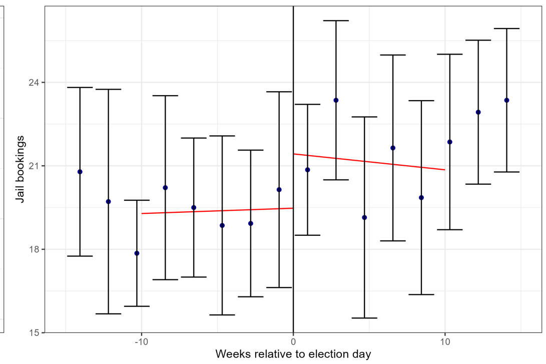
Table 15. Placebo test - 2021 data

Outcome	Slope change	Trend pre-election	Trend post-election
Police Behavior			
Police stops			
All Stops (crimes only)	3.715*	-	-
Police reports			
All Incident Reports (crime)	-3.000	+	-
Police arrests (SFPD)			
All arrests	0.073	+	+
All felony arrests	0.043	+	+
All misdemeanor arrests	-0.187	+	-
Residents Behavior			
Residents Calls			
Crime related	-5.36***	+	-
Non-crime related	-0.953	+	-
Residents Online Reports			
All residents' online reports	-4.248***	+	-
DA Behavior			
All charges	-0.091	+	-
All dismissals	-0.239*	+	+
Jail Population			
Bookings (SFPD)	0.068	0	-

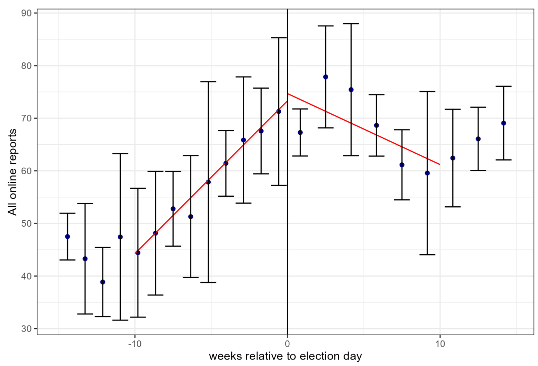
Note: All analyses utilize the rdrobust function to estimate the change in slope of the outcome concerning the weeks around June 7, 2021. We repeat the analysis of the 2022 data, replaced with 2021 data as a sanity test. The specification spans a 10-week bandwidth. All estimates rely on full police data: SFPD and other agencies.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



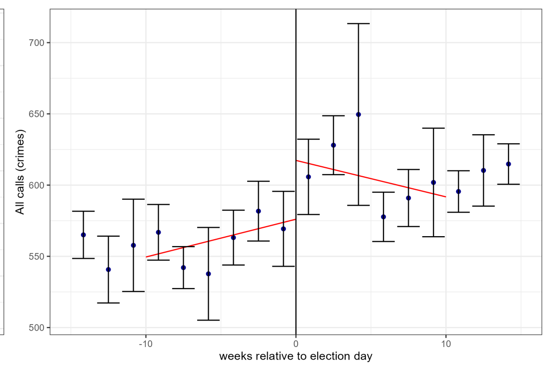
(a) Arrests



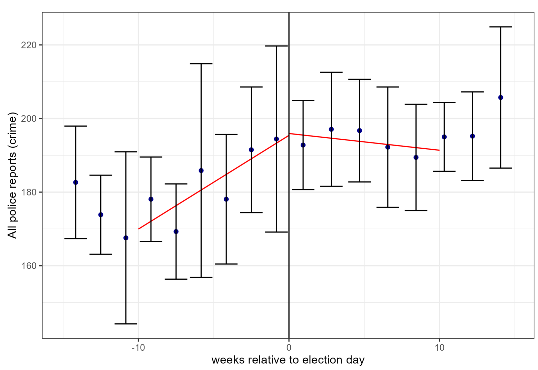
(b) Jail bookings by SFPD



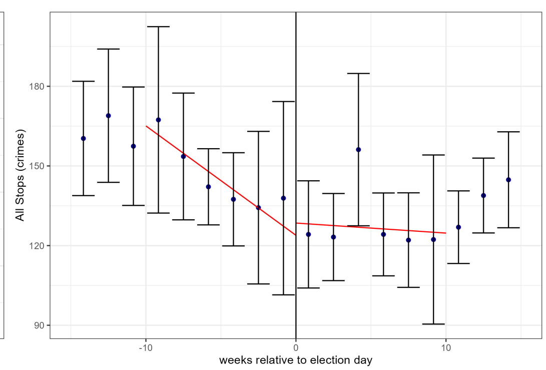
(c) Online residents reports



(d) Citizen 911 calls

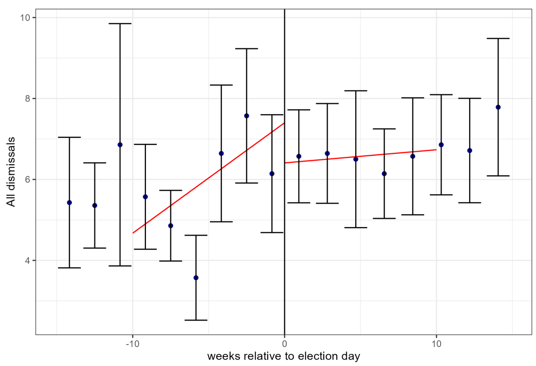


(e) Police reports (crime)

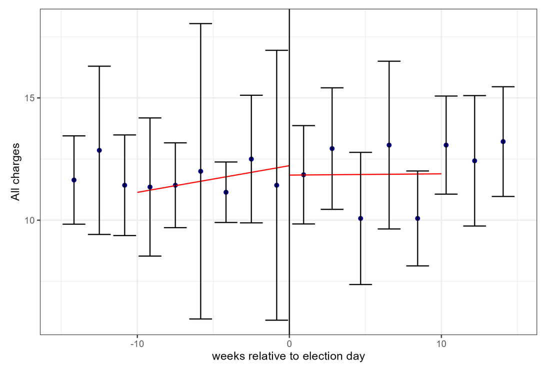


(f) Police stops

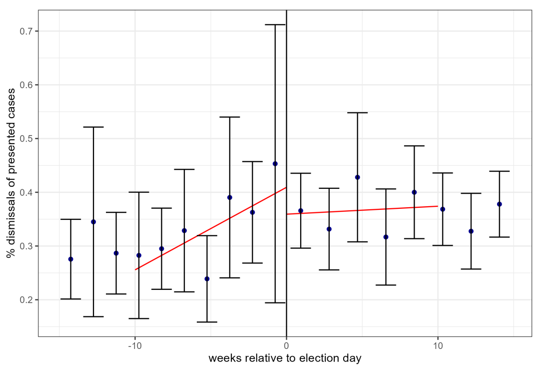
Figure 18. Main Placebo Results, weekly 2021
Note: Figure continued on the next page.



(g) Cases dismissed by the DA



(h) Cases charged by the DA



(i) Portion of dismissed cased out of arrests presented

Figure 18. Main Placebo Results, weekly 2021
Note: Januar 1st - Decmber 31st, 2021. The vertical line marks June 7th. Generated using the rdplot function in R's rdrobust package. The function uses the mimicking variance evenly-spaced method (esmv) to select the number of bins for the running variable to minimize the variance of the estimated treatment effect. The mean outcome variable and its standard error are calculated within each bin, with the latter used to generate 95% confidence intervals. Two local regression models are estimated, one for the period before the treatment week and one for the period after, using a bandwidth of 10 weeks to construct the fits.