

The Effect of Prosecutor Elections on Policing Patterns

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Abstract

The relationship between prosecutors and police is evolving, particularly as reform-oriented district attorneys (DAs) push for greater police accountability. This study examines police behavior before and after the San Francisco DA Chesa Boudin recall on June 7, 2022, analyzing whether officers altered enforcement patterns in response to political dynamics. Using a Regression Kink Design and data on stops, arrests, incident reports, prosecutorial decisions, and jail populations, we find a decline in police activity leading up to the recall, followed by an increase afterward—particularly in discretionary enforcement actions. Crime reporting remained relatively stable, suggesting changes in crime trends did not drive these shifts. Our findings highlight the interdependence between prosecutors and police, showing how law enforcement behavior can respond to political transitions. This underscores challenges in assessing prosecutorial policies and raises concerns about law enforcement resistance to accountability measures, emphasizing the need for institutional safeguards against politically influenced enforcement shifts.

1 Introduction

Historically, prosecutors and police departments have worked hand-in-glove. However, recent shifts in district attorney (DA) politics have disrupted this relationship. Increased electoral competitiveness and the rise of a reform-driven movement have led to the election of prosecutors who take a more critical stance on police accountability ([Wright et al., 2021](#); [Hessick and Morse, 2019](#); [Davis, 2019](#); [Sklansky, 2016, 2017](#); [Holland and Zeidman, 2023](#)). A growing body of research and reported incidents suggests that police may engage in de-policing when faced with public scrutiny and accountability efforts. In this context, the changing dynamics between officers and DAs, particularly progressive prosecutors committed to holding police accountable for misconduct, have the potential to significantly impact public safety.

To better understand the evolving dynamics between police and DAs, this paper examines police behavior in the context of prosecutor elections. Specifically, it explores the contentious relationship between the San Francisco Police Department (SFPD) and progressive District Attorney Chesa Boudin, who was elected in November 2019 and later recalled on June 7, 2022. This study investigates whether police altered their behavior in anticipation of or in response to the recall election, analyzing trends in the period leading up to and following the recall.

Using a Regression Kink Design and data on police activities (stops, calls, arrests), incident reports, prosecutors' charging behavior, and jail population, we demonstrate a pattern of declining police activity before the recall election, followed by an increase in activity intensity after the successful recall, with the jail population following a similar pattern. Crime reporting remained considerably stable throughout the study period. Overall, it is evident that police altered their behavior before and after the recall.

This paper contributes to the study of DA and police relationships, particularly in the context of elections where the incumbent DA is viewed unfavorably by officers. Unlike studies that focus solely on police reactions to unexpected events, this setting provides insight into their proactive behavior leading up to a highly anticipated but uncertain election. Additionally, this study cap-

tures multiple critical points of police behavior, offering a comprehensive view of incident progression through the CJS—from the initial police response to prosecutorial handling.

This paper speaks to the fundamental problem of interdependence in criminal justice administration. Prosecutors and police officers, each fundamentally responsible for distinct stages within the criminal justice procedure, have a conflict of interest; prosecutors, most notably, depend on police officers to bring in cases and evidence, yet are also responsible for prosecuting the police if officers break the law. In this regard, we provide evidence that measuring the effect of prosecutors' policies on crime is confounded by any changes in police behavior that affect prosecutors' ability to carry out their duties. For example, if in response to a prosecutor's office policy on drug-related charges, the police change their arrest rate, then any public safety outcome is the combined effect of the policy on charges and arrest decisions. Therefore, accounting for police enforcement and the DA–police relationship is essential when evaluating prosecutors and their policies.

Finally, this paper engages with societal concerns about how the system—and, in this case, DAs—can effectively hold police accountable given their complex dynamic and interdependence. These ties often give rise to two distinct but interconnected challenges: conflicts of interest, such as questionable collaborations and campaign contributions¹, and resistance to accountability, as seen in the de-policing behaviors demonstrated in this study. Both dynamics underscore the intricate nexus between prosecutors and law enforcement. Legal scholars, practitioners, and advocacy groups have called for regulatory measures to limit DA involvement in cases concerning local law enforcement officers ([Mazzone and Rushin, 2019](#); [Freeman, 1995](#); [Schwartz, 1969](#); [Hodson, 2018](#); [Levine, 2015](#)). However, in the vast majority of jurisdictions, cases implicating local police still fall under the purview of the local DA. This paper contributes to this conversation by showcasing the consequences of police and prosecutors' conflict of interest.

¹For 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](#)).

2 Background

2.1 Contextual Background

DAs are the heads of the prosecutor's office and elected officials who determine their jurisdiction's approach to criminal justice policy.² Traditionally, prosecutor elections were seen as apolitical and rarely contested, with incumbents winning until they chose to retire (Pfaff, 2017; Wright, 2014; Bibas, 2016; Bazelon, 2020). However, Wright et al. (2021), in a study of prosecutor elections across 200 high-population districts in the US between 2012 and 2020, found that the likelihood of an incumbent running unopposed "fell by roughly eight percent for each passing year". Similarly, Hessick and Morse (2019) collecting election results from the 2014 or 2016 cycles across 2,315 districts in 45 states, found that elections were more likely to be contested and competitive in urban jurisdictions.

As the elections became steadily more contested and competitive, DA candidates increasingly made political promises to transform the criminal justice system with a re-imagined vision of the DA's role (Wright et al., 2021; Davis, 2019). Colloquially, these reform-minded DAs became known as "progressive prosecutors." By the beginning of 2023, America's five most populated cities had elected progressive district attorneys (Hessick and Morse, 2019).³

Moreover, following highly publicized incidents of excessive police brutality, which sparked unprecedented protests and raised attention to police misconduct, a key component of many progressive DAs' agenda has been police accountability (Sklansky, 2016, 2017). Often sided with protesters, progressive prosecutors vowed to press charges against police officers zealously (Holland and Zeidman, 2023).

The progressive prosecutor movement might have unintended consequences. Stricter legal scrutiny

²American 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.

³These cities include Los Angeles, Philadelphia, Boston, New York, Chicago, and Houston. New York has five district attorneys, one for each county/borough. New York County (Manhattan) and Kings County (Brooklyn) have elected progressive prosecutors.

on police officers, a hallmark of progressive prosecutors' agendas, could lead officers to avoid certain activities, potentially affecting public safety ([Stashko and Garro, 2023](#)). This issue is evident in reported instances of the so-called "blue flu," a type of strike action undertaken by police officers in which many simultaneously use sick leave. Such actions have been observed during periods of heightened scrutiny, including calls to "defund the police" following George Floyd's murder and instances where officers faced prosecution ([Grim, 2020](#); [Hansen, 2020](#)).⁴ These responses, whether driven by rational caution or intentional resistance to accountability efforts, highlight the need to understand police behavior and its relationship with prosecutors' agendas to ensure the smooth operation of the CJS and advance criminal justice reforms.

2.2 The Case of San Francisco

This paper examines police performance in the context of prosecutor elections, underscoring how the political dynamics between prosecutors and police can influence criminal justice outcomes. It centers on the case of San Francisco, exploring the contentious relationship between the SFPD and the progressive District Attorney Chesa Boudin, who was successfully recalled 2.5 years into his term.

The relationship between Boudin and the SFPD was fraught from the start. His campaign, which advocated progressive reforms such as ending money bail and reducing mass incarceration, also vowed to hold police accountable for misconduct. In response, the San Francisco Police Officers Association launched paid advertisements labeling Boudin as "the #1 choice of criminals and gang members." Chesa Boudin was elected District Attorney on November 5, 2019. Just a month later, in December of that year, Boudin's office charged a police officer in the first known excessive-force prosecution in the city's history, while on June 5, 2020, the DA's office released an official statement announcing "New Appointment and New Policy Designed to Protect the

⁴In 1971, about 20,000 New York City police officers called in sick for five days, partially in response to the dismissal of a lawsuit that would have increased pay and provided back pay ([Sestanovich, 2016](#)). In 1981, officers of the Milwaukee Police Department staged a "blue flu" for two days, citing disregard from city officials ([The Associated Press, 1981](#)). In 2020, Atlanta police officers staged a sick-out to protest criminal charges against officers involved in the killing of Rayshard Brooks ([Hagen, 2020](#)).

Public From Police Misconduct and Abuse."⁵ 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 was set for June 7, 2022. If the recall election results force Boudin out of office, Mayor London Breed would get to choose his successor.⁶

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.⁷ The SFPD Chief said that: "trust between the two agencies was irrevocably damaged."⁸ At the time, Boudin's office was prosecuting six officers in five separate use-of-force cases.⁹

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 offi-

⁵"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.

⁶Mayor Breed supported Boudin's opponent during the 2019 election for DA. Boudin and Breed later clash (December of 2021) 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."

⁷Notice from the Chief of Police to DA Boudin, Feb. 2, 2022.

⁸SF Chronicle, Feb. 4, 2022.

⁹SF Chronicle, Feb. 2, 2022.

cers in patrol cars, standing by and watching as businesses were being burglarized, making no attempt whatsoever to intervene to arrest suspects." ([Holloway, 2023](#)).¹⁰

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; 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."¹¹

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.¹² 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.¹³

This documented tension and the political stakes surrounding the recall election provide a strong motivation to test empirically whether SFPD behavior systematically changed in the period leading up to and following June 7, 2022.

¹⁰In Portland, the police chief publicly called city cops to stop telling residents DA Mike Schmidt won't prosecute crimes ([Kavanaugh, 2023](#)).

¹¹[SF Chronicle, Feb. 19, 2022](#)

¹²["Who will replace Chesa Boudin as SF DA?" KRON4, Jul 7, 2022.](#)

¹³["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."](#)

2.3 Literature

The paper contributes to three strands of literature. First, it adds to the burgeoning literature on prosecutor-police dynamics, which reveals significant behavioral interdependencies. For example, [Stashko and Garro \(2023\)](#) demonstrates that police officers may recalibrate their use of lethal force following the ousting of an incumbent DA, likely due to uncertainties about their relationship with the new DA. Our work expands this discourse by demonstrating how prosecutor-police relationships influence routine policing outcomes and, in turn, affect jail incarceration.

Second, previous studies have examined how policing behaviors shift following high-profile events, such as police shootings or subsequent protests. Evidence suggests transient reductions in police stops post such incidents ([Mikdash and Zaiour, 2022](#)), with no corresponding short-term crime spikes ([Shjarback et al., 2017](#); [Abrams et al., 2022](#); [Cho et al., 2021](#)). In addition to changes in typical police activities, following George Floyd's murder, Minneapolis police exhibited a marked discontinuity in reporting race and gender data during stops—dropping from roughly 71% to 35%, a decline of approximately 36 percentage points ([DOJ, Civil Rights Division and USAO, District of Minnesota, Civil Division, 2023](#)). Building on this literature, our research highlights how policing responds to political landscapes, particularly in the context of DA elections and recalls, as observed in our case.

Finally, the nexus between accountability frameworks and police efficacy exhibits mixed results. 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](#)). This paper contributes to the literature by examining police behavior in the context of a progressive prosecutor, known for advocating and acting on police accountability, facing a recall election.

3 Data

To estimate the impact of DA Boudin’s recall on policing, prosecution, and San Francisco’s jail population, we combine four datasets: police stops and calls, incident reports (online and by police officers), arrests presented to the DA’s office, and jail population data (daily head count, and bookings). Figure 1 presents the four datasets we explore, how they relate to each other, and the discretion points at each stage. These datasets allow us to measure changes in how police and prosecutors use discretion throughout the encounter stages.

Police Stops and Calls. First, as shown in Figure 1, officers can either be dispatched to a scene by a resident-initiated 911 call or conduct an "on-view," where they choose to respond to events they see during their shift. We examine both on-view stops, in which officers have almost total discretion, and citizen-initiated 911 calls to ensure any changes in stops aren’t driven by shifts in crime activity or civilian demand for police services.

Data on police stops and calls comes from the "Law Enforcement Dispatched Calls for Service - Closed Calls" dataset, an SFPD-generated dataset available on the OpenDataSF portal. This dataset includes individual call-level data on service calls in San Francisco, originating either from 911 calls or from officers observing incidents in the field ("On-View").^{14,15} As shown in Panel A of Table 1, during our analysis period, SFPD received an average of 551 crime-related 911 calls and made about 92 crime-related stops per day, with nearly half of those being for public order offenses. The vast majority of stops are "passing calls," a radio code used by officers to log their location without taking further action. This can be in response to directives from the chain of command or at the officer’s discretion. Many occur at transit authority parking lots for

¹⁴Data 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>

¹⁵We use the call type description fields to categorize calls and on-view stops into different crime or non-criminal call types. We exclude irrelevant or rare call types, such as administrative calls (e.g., meetings), types of incidents that appear only in 911 calls, 311 calls, citizen standby calls, and non-criminal calls where police assist with 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 outside San Francisco police districts or handled by other agencies like the fire department or EMS.

directed theft abatement. "Passing calls" are informative because they represent a baseline level of highly discretionary activity that officers might easily increase or decrease in response to perceived scrutiny or changing political winds.

Police Incident Reports. After responding to a 911 call or making an on-view stop, officers exercise discretion in deciding whether to report a crime. Depending on the events and the officers' judgment, each call or stop may or may not result in a police incident report. In addition to 911 calls and on-view stops, citizens can also initiate and file incident reports. Depending on the crime type, some reports can be submitted online, while others require citizens to call or visit a police station to file with an officer.¹⁶

Police incident reports are recorded in the "Police Department Incident Reports: 2018 to Present" dataset, also available on OpenDataSF.¹⁷ Officers file the vast majority of incident reports, while non-emergency reports (property and public order) can be filed online by the public using SFPD's self-service reporting system.¹⁸ Panel B of Table 1 shows that, on average, 195 criminal incident reports are filed per day by SFPD officers or by civilians over the phone or in person—the vast majority for property crimes—with an additional 74 reports per day filed online by civilians.

Arrests. After police make a stop or respond to a call and determine that a crime has occurred, their next point of discretion is whether to make an arrest. If they do, it is then up to the DA's office to charge or decline the case.

The relevant dataset on arrests comes from the San Francisco District Attorney's Office, titled "District Attorney Actions Taken on Arrests Presented," available on OpenDataSF.¹⁹ It includes information on arrests presented to the SFDA since 2011 and the actions taken by the SFDA for

¹⁶For more information on how citizens can make a report, see: <https://www.sanfranciscopolice.org/get-service/police-reports>

¹⁷Data 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>

¹⁸We 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.

¹⁹Data source: <https://data.sfgov.org/Public-Safety/District-Attorney-Actions-Taken-on-Arrests-Present/czsm-3ei3>

each arrest. We first examine the number and types of arrests to study police behavior and discretion, followed by an analysis on DA’s charging decisions.²⁰ Panels A and B of Table 2 show that, on average, SFPD made about 18 arrests per day during our analysis period—around 14 felony arrests and four misdemeanor arrests—while the SFDA discharged approximately 28% of them.

Jail Population. Regarding changes in the jail population, we use data from two different sources. The first dataset is obtained from the Jail Data Initiative operated by the NYU Public Safety Lab.²¹ The data consists of daily detainee-level information 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, the second dataset used is from the San Francisco Sheriff’s Department and records the number of daily bookings. Panel C of Table 2 shows that the average daily inmate population is around 750 people, with approximately 28 bookings per day.

4 Empirical strategy

This study leverages quasi-experimental variation and employs a Regression Kink Design (RKD) to examine behavioral responses across the criminal justice system surrounding the June 7, 2022, recall election of the San Francisco District Attorney. A key component of our analysis is that the treatment is the recall election and the results known on election night, though no immediate regime change occurred that day. Boudin, the DA who lost the recall, remained in office for four more weeks until the mayor appointed an interim DA. Unlike a formal policy change, which might prompt immediate and simultaneous shifts in officer behavior, we anticipate a progressive and escalating shift following Boudin’s loss, consistent with the pattern leading up to the recall. This event unfolded within a context of mounting tensions during the weeks preceding election day, with the rocky relationship between Boudin and the SFPD steadily deteriorating, as our results will demonstrate. Similarly, we expect the recall results to trigger gradual behavioral

²⁰We exclude arrests made by agencies other than the SFPD.

²¹Data source: <https://jaildatainitiative.org/> Dashboard: <https://publicsafetylab.org/jail-data-initiative>

changes among law enforcement personnel. The gradual nature of these adjustments makes a regression kink design more suitable than a sharp discontinuity design for capturing these effects.

The key identifying assumption underlying our RKD approach is that, absent the recall election, the relationship between time and our outcomes would have maintained a smooth slope through the election date. This assumption is more plausible than a sharp discontinuity assumption, given that the election and its outcome could affect behavior gradually through informal channels rather than through immediate policy directives. If this assumption holds, the difference in the slopes on either side of the election date can be attributed to the effect of the prosecutor’s election on police behavior. 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.

To estimate the effect of the recall election on various criminal justice outcomes Y_{it} , we implement a two-stage estimation procedure. In the first stage, we residualized our outcomes to account for systematic patterns in criminal justice activities:

$$Y_{it} = \alpha + \gamma_d + \delta_w + \varepsilon_{it} \quad (1)$$

where γ_d represents day-of-week fixed effects and δ_w controls for week-of-year effects. This residualization addresses potential confounding from seasonal and weekly cyclical patterns documented in prior work (Carr and Packham, 2019). In the second stage, we estimate our main regression kink specification:

$$\varepsilon_{it} = \beta_0 + \beta_1 W_{it} + \beta_2 After_{it} + \beta_3 (W_{it} * After_{it}) \quad (2)$$

Where W_{it} is the running variable measuring weeks from the election date, $After_{it}$ is an indicator for post-election observations, and β_3 is our coefficient of interest, measuring the change in slope at the election threshold; it captures the change in the weekly trend (slope) of the outcome

variable after the recall election, compared to the trend before it. We implement our RKD estimator using local linear regression with a uniform kernel and a baseline bandwidth of 10 weeks on either side of the election date.

We conduct several robustness checks. First, we examine placebo outcomes unlikely to be affected by police behavior, including citizen-initiated calls for service and online crime reports. These tests help distinguish changes in police behavior from underlying shifts in criminal activity or citizen reporting. Second, we provide bandwidth sensitivity analysis, examining results across bandwidths ranging from 5 to 15 weeks; this balances capturing the post-event trend change against potential contamination from later events. Finally, we implement our analysis using prior-year data as a placebo test.

5 Results

5.1 Police Behavior.

The daily counts of SFPD officer-initiated stops, categorized as a crime, were trending downward during the ten weeks leading up to the recall election and immediately began increasing after DA Boudin was recalled (Panel A of Table 3, Figure 2). Prior to the election, overall crime-related stops were declining at a rate of 0.17 stops per week below seasonal expectations. After the election, this pattern reversed dramatically, with stops increasing at a rate of 0.38 stops per week—representing a significant shift of 0.558 in the slope ($p < .001$). To put this in perspective, this means that in the ten weeks following the election, changes in police behavior led to approximately 30.25 more stops compared to what would have been expected under the pre-intervention trend.²² This represents a meaningful change in the underlying trend of police behavior, shifting from a pattern of gradually decreasing stops to one of consistently increasing stops above seasonal expectations. This pattern is driven by stops related to traffic and public order incidents (and, to a lesser degree, to property-related incidents). These are the categories for which officers have the most discretion in making a stop, compared to violent crime.

²²Total additional stops= $0.558 \times (1+2+3+\dots+10)$

If this increase was driven by underlying criminal activity or citizen demand for police services, we would likely see a corresponding increase in calls to the police or citizen-filed online criminal incident reports. However, we find no statistically significant trend break in these outcomes (Panel B of Tables 3 and 4; Figures 3, 4, and 6). In addition, we do not observe any change in police officers' reports, except for a significant jump in drug-related reports four weeks after the recall election (Panel A of Table 4 and Figure 5), suggesting that officers changed their behavior on drug-related reports when the interim DA replaced Boudin (July 2022).

Notably, we find the same trend for SFPD arrests: a decrease before the election followed by an immediate increase after the recall (Table 5 and Figure 7). For SFPD, total arrests showed a shift from decreasing by 0.26 arrests per week before the election to increasing by 0.64 arrests per week after—a significant change in the trajectory of 0.90 arrests per week ($p < .001$). This means that by ten weeks after the election, SFPD made 49.5 more arrests than expected under the pre-intervention trend. This result is driven by property-related arrests and arrests categorized as felonies.

5.2 Prosecutors Behavior.

Next, we explore whether the recall election and the resulting increase in arrests influenced the DA's propensity to charge cases presented by the SFPD. (Table 6, and Figure 9). 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. Our analysis finds a striking reversal in case dismissals following the recall election. For SFPD arrests, dismissals shifted from decreasing by 0.23 cases per week to increasing by 0.26 cases per week—a significant change of 0.49 cases per week ($p < .001$). This shift was particularly pronounced for felony cases, which showed a strong reversal from -0.13 to 0.19 cases per week ($p < 0.01$), while misdemeanor dismissals showed a smaller but still significant increase ($p < 0.05$). Importantly, this increase in case dismissals began on the recall election date and continued after interim DA

Jenkins was appointed about four weeks later.

However, we also observe a positive but noisy increase in new charges, driven entirely by felony charges (shifting from -0.08 to 0.3 cases per week, $p < 0.05$). This is consistent with the increase in felony arrests by the SFPD and suggests that the surge in dismissals is primarily a results of the overall increase in arrests rather than a change in charging strategy. This interpretation is further supported by a small but significant increase in the percentage of arrests resulting in dismissals (1.46 percentage points, $p < 0.05$), suggesting a subtle shift in how cases were processed following the recall.

5.3 Jail Population

Lastly, we examine how changes earlier in the criminal justice pipeline affected the jail population. First, we find a significant shift in the trajectory of daily jail bookings by the SFPD following the recall, with an increase of 0.99 bookings per week ($p < .001$) (Table 7 and Figure 11), aligning with the 0.9 additional arrests per week observed earlier. Next, examining the overall jail population—measured by the 5 AM count of individuals in custody—we observe a striking reversal (Table 7 and Figure 10): from decreasing by about ten people per week before the recall to increasing by 6.4 people per week after—a highly significant shift of 16.3 people per week ($p < .001$).

To further explore the dynamics behind the increasing jail population post-recall, we examine trends in the duration of custody. Figure 12 illustrates a pronounced reduction in the average jail stay coinciding with a surge in inmate counts. After the recall, the average person in jail is released much faster (from about 300 days till release to less than 50). To formally test the relationship between the daily jail population, the recall timing, and this average release duration measure, we employ a linear regression model specified as:

$$\text{AverageDays}_t = \beta_0 + \beta_1 \text{Population}_t + \beta_2 \text{afterRecall} + \beta_3 \text{Population}_t \times \text{afterRecall} + \varepsilon_t \quad (3)$$

Where $AverageDays_t$ is the average jail stay duration (in days) at time t ; $Population_t$ is the inmate count at time t , and $afterRecall$ is a binary indicator, assigned a value of 1 post-June 7 (the recall date) and 0 otherwise. The regression results are presented in Table 8. The model explains approximately 90% of the variance in average jail duration ($R^2 = 0.899$). The model shows a statistically significant negative interaction term ($\beta_3 = -0.1$, $p < 0.001$), indicating a substantial shift in the relationship between population size and average release duration after the recall. Higher populations were associated with slightly shorter average jail stay durations before June 7 ($\beta_1 = -0.228$, $p < 0.001$); this relationship became considerably stronger post-recall. After June 7, higher jail populations were associated with a significantly steeper decline in average duration (slope = $\beta_1 + \beta_3 \approx -1.228$). This finding is consistent with the hypothesis that the post-recall surge in jail bookings involved individuals processed for offenses carrying shorter jail stays or whose cases were dismissed more frequently (as suggested by findings in Section 5.2), thereby gradually reducing the calculated average duration of the released population.

5.4 Robustness

Figure 13 shows the robustness of the main results to a variety of alternate bandwidths from 5 to 15 weeks. Moreover, we replicate our analysis using data from the previous year (2021) as a counterfactual scenario, where the recall election had not occurred. Table 9 display these results.

6 Discussion

This paper explores the contentious relationship between the SFPD and reform-minded District Attorney Chesa Boudin, examining police behavior around his recall election. Overall, we find a decline in police activity in the weeks leading up to the recall, followed by an increase afterward, particularly in activities where officers have high discretion.

First, after the recall, police stops increased, primarily for traffic and public order offenses (e.g., sitting/lying on sidewalks, vandalism, noise, trespassing, dumping). This may be partially due to Boudin’s prosecution practices, which dismissed minor offenses (Matt, 2019) and cases involving

contraband found in pretextual traffic stops (Matt, 2020),²³ prompting police to increase such stops in anticipation of a potential policy reversal. However, since Boudin remained in office for another month before being replaced, it is unlikely that officers adjusted their behavior solely in expectation of an immediate policy change.

Furthermore, the increase in police stops did not correspond with a rise in police reports, except for a slight increase in reports for drug offenses (categorized under public order in the police stops analysis). Crime reporting remained relatively stable throughout the study period. This raises questions about the quality of policing, as the changes in marginal activity do not seem to have much effect on crime reporting (Cho et al., 2021).

Next, while crime reports changed little after the recall, police made more arrests, primarily for property offenses and felonies. The pattern of arrests differs from the increase in stops and incident reports, which were concentrated on public order, traffic, and drug offenses. This suggests that for less serious, often victimless offenses, officers have more discretion over whether to make a stop or file a report. In contrast, for more serious offenses involving a victim, where a report has already been filed, the key decision is whether to proceed with an arrest.

In line with the post-recall increase in arrests, the rise in jail bookings closely follows, indicating that the rise in the jail population is almost entirely driven by police activity and additional arrests. Additionally, the decline in jail stay duration after the recall suggests a shift toward more frequent arrests for offenses associated with shorter stays. However, considering the increase in felony arrests—typically linked to longer stays—the reduced jail stay duration implies that many of these new felony arrests may have been dismissed by prosecutors. This interpretation is further supported by the observed rise in felony dismissals after the recall.

This increase in case dismissals could stem from several factors: uncertainty about the length of the lame-duck period may have made the DA's office hesitant to pursue marginal cases given impending personnel changes; the surge in arrests may have caused capacity constraints to become

²³<https://sfdistrictattorney.org/wp-content/uploads/2020/11/Declination-of-Contraband-Charges-Based-on-Pretextual-Stops.pdf>

binding; or the changing composition of arrests may have led to lower-quality cases with insufficient evidence for prosecution. Regardless of the cause, the rise in dismissals further suggests that San Francisco's jail population increase was driven more by heightened police activity than by changes within the DA's office.

Moreover, the rise in case dismissals provides further evidence that officers' behavior couldn't have changed solely in response to shifts in the DA's prosecution practices—specifically, an increased likelihood of prosecution. It could be posited, and it often was, that officers were intentionally moderating their enforcement efforts before the recall, believing their arrests would not lead to charges. They might then logically intensify their efforts post-recall under the assumption that prosecutions would increase. Yet, this assumption conflicts with two important realities: first, officers are rarely informed of the prosecutorial fate of their arrests on an individual basis, and second, the data contradict the belief that prosecutions would increase after the recall—the rate of arrests resulting in charges declined, if anything.

These phenomena, combined with the uncertainty surrounding the period between the recall election and DA Jenkins's appointment—when any immediate change in prosecutorial practices was unclear—makes it difficult to determine whether police behavior was a response to a mistaken belief about the changing likelihood of charges or if it was a strategic reduction in enforcement to potentially impact the election outcome, followed by a return to usual levels of effort once the electoral process concluded.

Finally, while formal hypothesis tests around the election of interim DA Jenkins to a full term in the November general election are beyond the scope of this paper, Figure 12 shows that the upward trend in jail population following the recall appears to have reversed after her election. These trends provide suggestive evidence that criminal justice enforcement in San Francisco continued to be responsive to political events.

7 Conclusion

This study examines the complex and evolving relationship between police and prosecutors, particularly in the context of district attorney elections. Focusing the contentious dynamic between the SFPD and reform-minded District Attorney Chesa Boudin, it investigates whether officers altered their enforcement patterns in anticipation of or response to his recall on June 7, 2022.

We find a decline in police activity leading up to the recall, followed by an increase post-recall, particularly in activities where officers have high discretion. Our findings provide evidence consistent with a strategic shift in police activity, highlighting the influence of political dynamics on law enforcement behavior. This suggests officers may adjust their behavior based on perceived prosecutorial priorities or incentives to shape election outcomes, rather than solely responding to crime patterns or policy changes.

Our findings contribute to the broader discussion on the interdependence between law enforcement and DAs, leading to two key takeaways. First, this relationship complicates the evaluation of prosecutorial policies, as police discretion can confound the perceived effects of policy changes on public safety. Therefore, any assessment of a prosecutor's impact on crime must account for potential shifts in police behavior that may either support or undermine prosecutorial initiatives. Finally, beyond its research implications, this study underscores key policy challenges in police accountability. Conflicts of interest between DAs and police, along with law enforcement's ability to adjust enforcement as a form of resistance, hinder accountability. Addressing these issues requires institutional safeguards to ensure impartial policing while allowing prosecutors to uphold justice without undue reliance on or opposition from law enforcement.

References

- Abrams, David S, Hanming Fang, and Priyanka Goonetilleke**, “Do cops know who to stop? assessing optimizing models of police behavior with a natural experiment,” *National Bureau of Economic Research*, 2022.
- Ali, Mir Usman and Sean Nicholson-Crotty**, “Examining the accountability-performance link: The case of citizen oversight of police,” *Public performance & management review*, 2021, 44 (3), 523–559.
- Ba, Bocar A and Roman Rivera**, “The effect of police oversight on crime and allegations of misconduct: Evidence from Chicago,” *University of Pennsylvania, Institute for Law & Economics Research Paper*, 2019, (19-42).
- Bazon, Emily**, *Charged: The new movement to transform American prosecution and end mass incarceration*, Random House Trade Paperbacks, 2020.
- Bibas, Stephanos**, “Restoring Democratic Moral Judgment Within Bureaucratic Criminal Justice,” *Northwestern University Law Review*, 2016, 111, 1677.
- Carr, Jillian B and Analisa Packham**, “SNAP benefits and crime: Evidence from changing disbursement schedules,” *Review of Economics and Statistics*, 2019, 101 (2), 310–325.
- Cho, Sungwoo, Felipe Gonçalves, and Emily Weisburst**, “Do Police Make Too Many Arrests? The Effect of Enforcement Pullbacks on Crime,” *IZA Institute of Labor Economics*, 2021.
- Davis**, “Reimagining Prosecution: A Growing Progressive Movement,” *UCLA Criminal Justice Law Review*, 2019, 3 (1).
- Devi, Tanaya and Roland G Fryer Jr**, “Policing the police: The impact of "pattern-or-practice" investigations on crime,” Technical Report, National Bureau of Economic Research 2020.

DOJ, Civil Rights Division and USAO, District of Minnesota, Civil Division, “Investigation of the City of Minneapolis and the Minneapolis Police Department,” Technical Report, United States Department of Justice June 16 2023. Accessed: 2023-10-04.

Freeman, Alexa P, “Unscheduled departures: The circumvention of just sentencing for police brutality,” *Hastings LJ*, 1995, 47, 677.

Grim, Andrew, “What is the ‘blue flu’ and how has it increased police power?,” *Washington Post*, July 1 2020. Accessed: 2023-10-04.

Hagen, Lisa, “Interim Police Chief Asks Atlanta Officers To Return, As Some Call Out Sick,” *WABE*, June 6 2020. Accessed: 2025-02-24.

Hansen, Zachary, “170 Atlanta police officers called out sick during ‘Blue Flu’ protests, records show,” *The Atlanta Journal-Constitution*, June 26 2020. Accessed: 2023-10-04.

Hessick, Carissa Bryne and Alison Rossi, “Op-Ed: California voters deserve to know who is bankrolling our district attorneys,” *Los Angeles Times*, Mar. 29 2018. Accessed: 2023-10-02.

Hessick, Carissa Byrne and Michael Morse, “Picking prosecutors,” *Iowa Law Review*, 2019, 105, 1537.

Hodson, Alexandra, “The American injustice system: The inherent conflict of interest in police-prosecutor relationships & how immunity lets them get away with murder,” *IDAHO L. REV.*, 2018, 54, 563.

Holland, Brooks and Steven Zeidman, “Progressive Prosecutors or Zealous Defenders, from Coast-to-Coast,” *American Criminal Law Review*, 2023, 60.

Holloway, Doni, “The Progressive Prosecutor Movement with Chesa Boudin,” Why Is This Happening? The Chris Hayes Podcast Sept. 21 2023. Accessed: 2023-10-04.

Kavanaugh, Shane Dixon, “Portland police chief to city cops: Stop telling residents DA Mike Schmidt won’t prosecute crimes,” *The Oregonian/OregonLive*, Aug. 8 2023. Accessed: 2023-10-04.

Levine, Kate, “Who Should’t Prosecute the Police,” *Iowa L. Rev.*, 2015, *101*, 1447.

Matt, “Boudin Will Not Prosecute Prostitution, Public Camping, And Other ‘Quality-Of-Life Crimes’ Once Sworn In,” *SFist*, Nov. 16 2019.

—, “Boudin to Stop Prosecuting for Contraband Seized at Traffic Stops, End Sentence Enhancements,” *SFist*, Feb. 29 2020.

Mazzone, Jason and Stephen Rushin, “State Attorneys General as Agents of Police Reform,” *Duke LJ*, 2019, *69*, 999.

Mikdash, Maya, “The Impact of Internal Oversight on Arrest and Use of Force,” in “2022 AP-PAM Fall Research Conference” APPAM 2022.

— **and Reem Zaiour**, “Does (All) Police Violence Cause De-policing? Evidence from George Floyd and Police Shootings in Minneapolis,” *AEA Papers and Proceedings*, May 2022, *112*, 170–73.

of the Mayor, Office, “Mayor London Breed Announces Appointment of Brooke Jenkins to Serve as San Francisco District Attorney,” July 7 2022. Accessed: 2023-10-04.

Pfaff, John, *Locked in: The true causes of mass incarceration-and how to achieve real reform*, Basic Books, 2017.

Schwartz, Louis B, “Complaints Against the Police: Experience of the Community Rights Division of the Philadelphia District Attorney’s Office,” *U. Pa. L. Rev.*, 1969, *118*, 1023.

Sestanovich, Clare, “A Short History of Police Protest,” *The Marshall Project*, 2016. Retrieved November 16, 2016.

Shjarback, John A, David C Pyrooz, Scott E Wolfe, and Scott H Decker, “De-policing and crime in the wake of Ferguson: Racialized changes in the quantity and quality of policing among Missouri police departments,” *Journal of criminal justice*, 2017, 50, 42–52.

Sklansky, David Alan, “The changing political landscape for elected prosecutors,” *Ohio St. J. Crim. L.*, 2016, 14, 647.

—, “The progressive prosecutor’s handbook,” *UC Davis L. Rev. Online*, 2017, 50, 25.

—, “The Problems With Prosecutors,” *Annual Review of Criminology*, 2018, 1 (1), 451–469.

Stashko, Allison and Haritz Garro, “Prosecutor Elections and Police Killings,” 2023. Unpublished manuscript.

The Associated Press, “Milwaukee Police Strike After 2 Officers Are Slain,” *The New York Times*, Dec. 24 1981. Accessed: 2025-02-24.

Tonry, Michael, “Prosecutors and Politics in Comparative Perspective,” *Crime and Justice*, 2012, 41, 1–33.

Westervelt, Eric, “Are prosecutors too cozy with police? Some DAs say campaign contributions need to end,” *National Public Radio*, June 18 2020. Accessed: 2023-10-04.

Wright, Ronald F, “Beyond prosecutor elections,” *SMU Law Review*, 2014, 67, 593.

—, **Jeffrey L Yates, and Carissa Byrne Hessick**, “Electoral Change and Progressive Prosecutors,” *Ohio St. J. Crim. L.*, 2021, 19, 125.

8 Tables and Figures

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

	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Stops (On View)						
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						
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
Incident Reports (Not Online)						
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
Online Incident Reports						
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 2. Summary Statistics: Arrests, DA, and Jail Population, daily level

	weeks (-10 to +10)		weeks (-10)		weeks (0 + 10)	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
SFPD Arrests						
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
DA action of SFPD Arrests						
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
Jail Population and Bookings						
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 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 3. Regression Discontinuity Results for Stops and Calls

	All	'Passing'				Public	
Panel A: Stops	Crimes	Calls	Violent	Property	Traffic	Order	
Conventional	0.558*** (0.108)	0.261 (0.353)	-0.006 (0.017)	0.063* (0.026)	0.234*** (0.047)	0.267*** (0.064)	
Slope (Left)	-0.17	-0.12	-0.01	-0.03	-0.05	-0.08	
Slope (Right)	0.38	0.14	-0.01	0.03	0.18	0.19	
Panel B: Calls	All	Not				Public	Alarm
	Crimes	Crimes	Violent	Property	Traffic	Order	
Conventional	-0.027 (0.372)	-0.054 (0.075)	-0.083 (0.117)	0.081 (0.149)	-0.008 (0.037)	-0.018 (0.169)	-0.033 (0.062)
Slope (Left)	-0.07	-0.03	-0.04	-0.04	-0.00	0.01	-0.01
Slope (Right)	-0.10	-0.08	-0.12	0.04	-0.01	-0.01	-0.04
N (Left)	5709	5709	5709	5709	5709	5709	5709
N (Right)	2321	2321	2321	2321	2321	2321	2321
Effective N (Left)	770	770	770	770	770	770	770
Effective N (Right)	847	847	847	847	847	847	847

Notes. All outcomes are residualized by regressing the raw counts on day-of-week and week-of-year fixed effects to account for seasonal patterns. The running variable is weeks relative to June 7, 2022, with a uniform kernel and bandwidth of 10 weeks on either side of the cutoff date. Estimates represent the change in slope of the relationship between time and each outcome at the cutoff, using a linear specification ($p=1$). + $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ significance level.

Table 4. Regression Discontinuity Results for police reports

	All	Not				Public	
Panel A: Police Reports	Crimes	Crimes	Violent	Property	Traffic	Order	Drugs
Conventional	0.234+ (0.135)	0.017 (0.025)	-0.004 (0.043)	0.150 (0.093)	0.017* (0.008)	0.002 (0.040)	0.069** (0.024)
Slope (Left)	-0.09	-0.00	-0.01	-0.09	-0.00	0.00	0.01
Slope (Right)	0.15	0.01	-0.01	0.06	0.02	0.00	0.08
Panel B: Online Reports	All					Public	
	Reports			Property		Order	
Conventional	-0.045 (0.094)			-0.035 (0.088)		-0.010 (0.017)	
Slope (Left)	-0.07			-0.06		-0.01	
Slope (Right)	-0.11			-0.09		-0.02	
N (Left)	5190	5190	5190	5190	5190	5190	5190
N (Right)	2110	2110	2110	2110	2110	2110	2110
Effective N (Left)	700	700	700	700	700	700	700
Effective N (Right)	770	770	770	770	770	770	770

Notes. All outcomes are residualized by regressing the raw counts on day-of-week and week-of-year fixed effects to account for seasonal patterns. The running variable is weeks relative to June 7, 2022, with a uniform kernel and bandwidth of 10 weeks on either side of the cutoff date. Estimates represent the change in slope of the relationship between time and each outcome at the cutoff, using a linear specification ($p=1$). + $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ significance level.

Table 5. Regression Discontinuity Results for Arrests

	All arrests	Felony arrests	Misdemeanor arrests	Violent	Property	Traffic	Public Order	Drugs	Other
Conventional	0.9022*** (0.2372)	0.7944*** (0.2122)	0.1078 (0.123)	0.2892 ⁺ (0.1623)	0.3316** (0.1093)	0.0121 (0.022)	0.0091 (0.0664)	0.0424 (0.0927)	0.2675** (0.0897)
Slope Left	-0.26	-0.23	-0.02	-0.11	-0.21	-0.02	0.01	0.15	-0.09
Slope Right	0.64	0.56	0.08	0.18	0.12	-0.01	0.02	0.19	0.18
N (Left)	519	519	519	519	519	519	519	519	519
N (Right)	211	211	211	211	211	211	211	211	211
Effective N (Left)	70	70	70	70	70	70	70	70	70
Effective N (Right)	77	77	77	77	77	77	77	77	77

Notes. All outcomes are residualized by regressing the raw counts on day-of-week and week-of-year fixed effects to account for seasonal patterns. The running variable is weeks relative to June 7, 2022, with a uniform kernel and bandwidth of 10 weeks on either side of the cutoff date. Estimates represent the change in slope of the relationship between time and each outcome at the cutoff, using a linear specification ($p=1$). ⁺ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ significance level.

Table 6. Regression Discontinuity Results for DA Actions

	All charges	All dismissals	Felony Charges	Misdemeanor Charges	Felony Dismissals	Misdemeanor Dismissals	% dismissals of arrests
Conventional	0.3082 (0.1951)	0.4926*** (0.1433)	0.3766* (0.1639)	-0.0684 (0.0851)	0.3177** (0.117)	0.1749* (0.076)	0.0146* (0.007)
Slope Left	-0.01	-0.23	-0.08	0.07	-0.13	-0.1	-0.01
Slope Right	0.3	0.26	0.3	0	0.19	0.08	0
N (Left)	519	519	519	519	519	519	519
N (Right)	211	211	211	211	211	211	211
Effective N (Left)	70	70	70	70	70	70	70
Effective N (Right)	77	77	77	77	77	77	77

Notes. All outcomes are residualized by regressing the raw counts on day-of-week and week-of-year fixed effects to account for seasonal patterns. The running variable is weeks relative to June 7, 2022, with a uniform kernel and bandwidth of 10 weeks on either side of the cutoff date. Estimates represent the change in slope of the relationship between time and each outcome at the cutoff, using a linear specification ($p=1$). ⁺ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ significance level.

Table 7. Regression Kink Design Results for Jail Population and Bookings

	Population	Bookings (all)	Bookings (SFPD)
Conventional	16.276*** (0.358)	1.068*** (0.233)	0.991*** (0.208)
Slope (Left)	-9.84	-0.25	-0.24
Slope (Right)	6.44	0.82	0.75
N (Left)	146	154	518
N (Right)	203	210	210
Effective N (Left)	62	70	70
Effective N (Right)	73	77	77

Note: The running variable is weeks relative to the election date. Dependent variables (daily counts) are listed in the columns. The 'Conventional' row reports the estimated change in the slope (kink) at the threshold. Estimates were obtained using local linear regression (polynomial order $p=1$) with a uniform kernel and a 10-week bandwidth on each side of the threshold. Outcomes were residualized prior to estimation to account for day-of-week and week-of-year effects. Robust standard errors, clustered at the week level, are reported in parentheses. 'Slope (Left)' and 'Slope (Right)' show the estimated linear trends just before and just after the threshold, respectively. 'N' reports the total number of daily observations; 'Effective N' reports the number of observations receiving non-zero weight in the local regression estimator. Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8. Regression: Average Jail Stay Duration, Population, and Recall Election

Dependent Variable: Average Duration (Days) of Current Jail Population				
Variable	Estimate	Std. Error	t value	Pr(> t)
Intercept	731.09	23.72	30.82	<0.001
Jail Population (Head Count)	-0.23	0.03	-7.45	<0.001
After Recall (June 7 = 1)	683.45	36.96	18.49	<0.001
Population $\times$ After Recall	-1.00	0.05	-20.95	<0.001

$N = 370$; $R\text{-squared} = 0.899$; $Adj. R\text{-squared} = 0.898$

Notes. OLS regression results. Standard errors are shown next to estimates. The dependent variable is the mean duration (days) for all inmates in jail on each date. Before the recall, higher jail population was associated with slightly shorter average stays (-0.23 days per additional inmate). After the recall, this relationship became substantially stronger, with each additional inmate associated with a 1.23-day decrease in average duration (-0.23 + -1.00). The model explains approximately 90% of the variation in average jail duration. All coefficients are significant at $p < 0.001$.

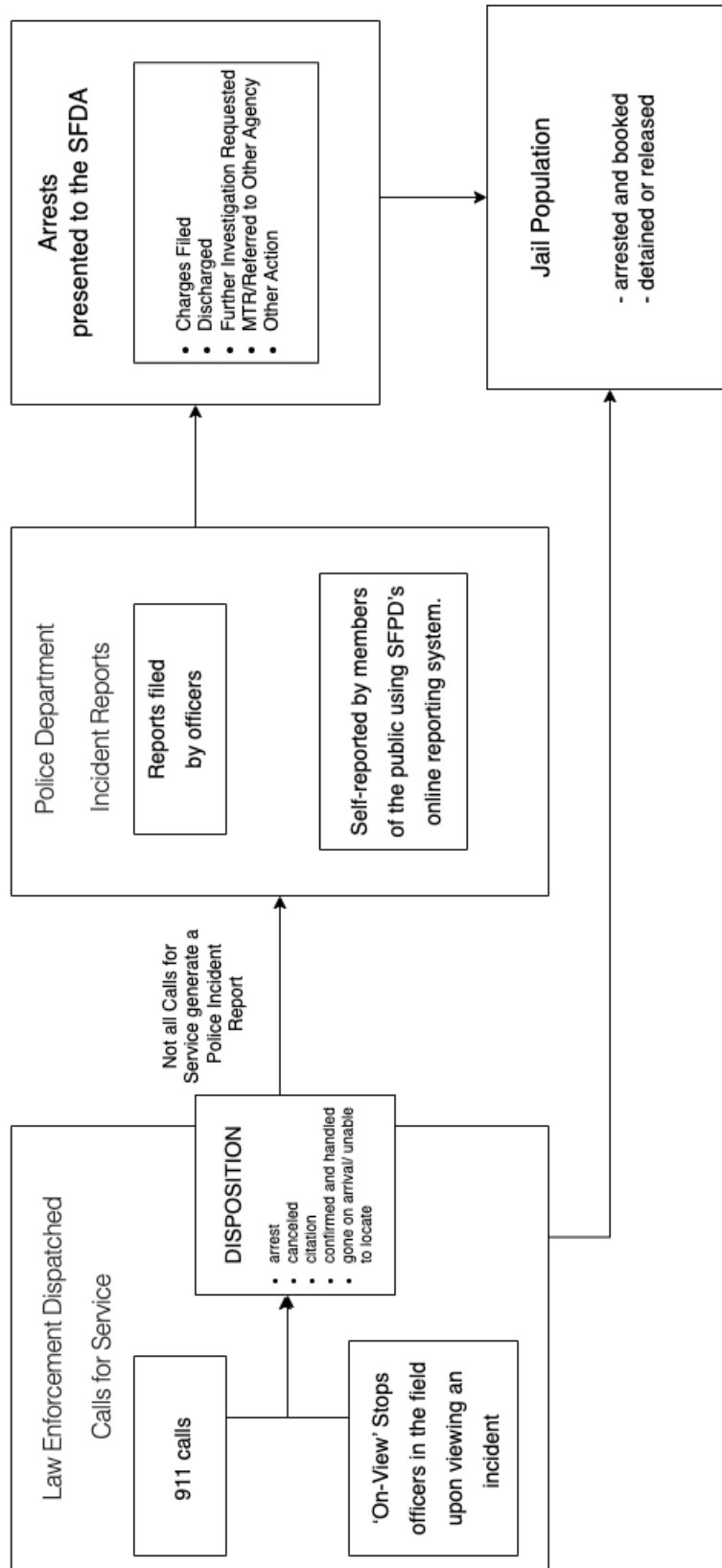


Figure 1. Discretion Points at Each Stage of a Criminal Incident

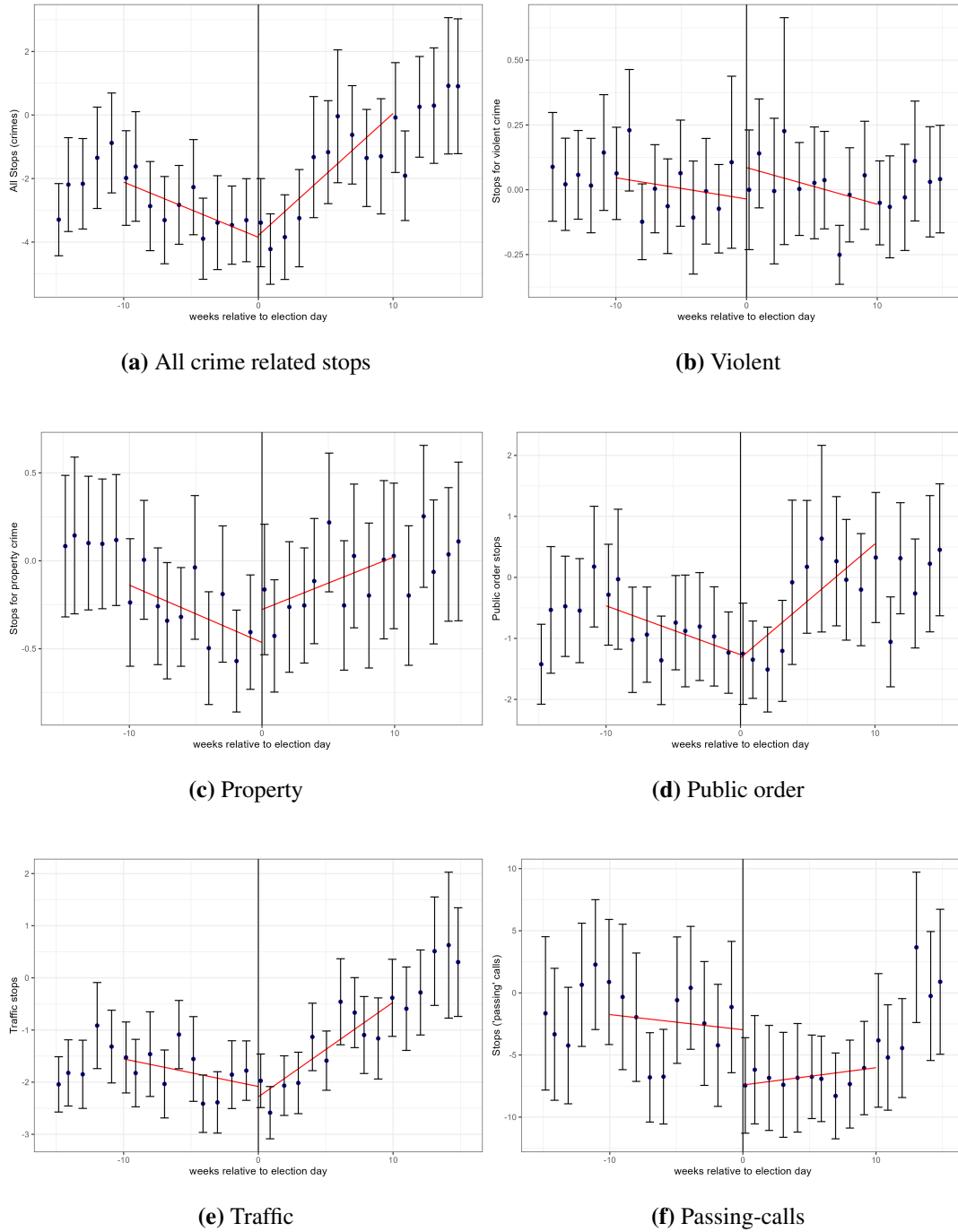


Figure 2. Officers' Stops, weekly analysis

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.

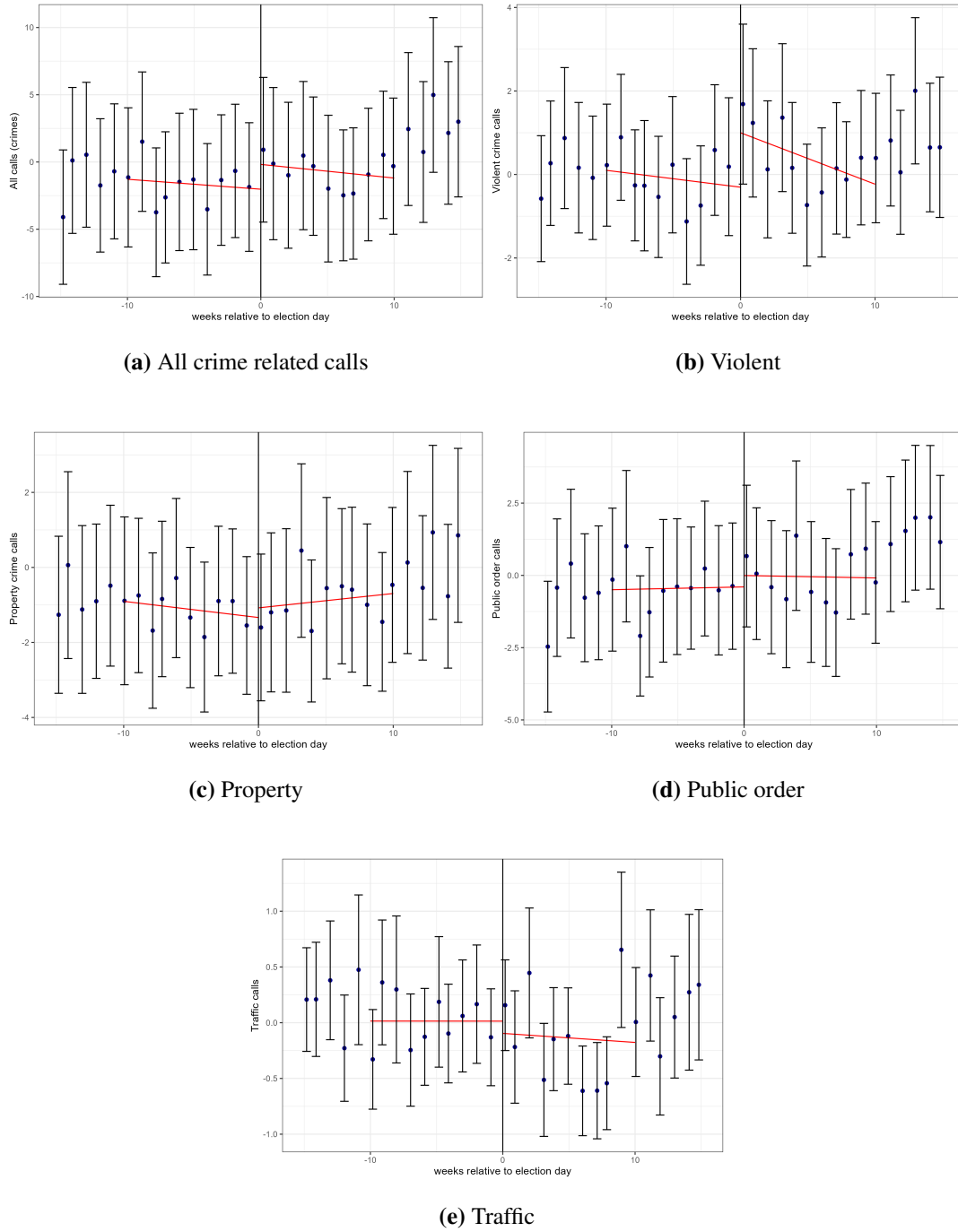
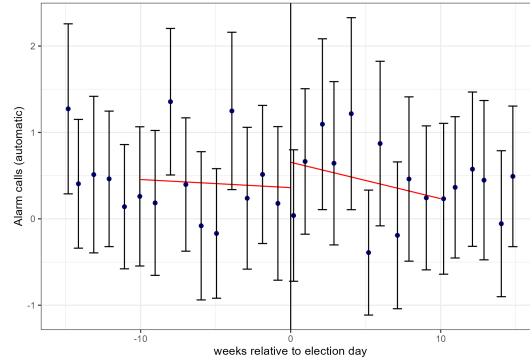
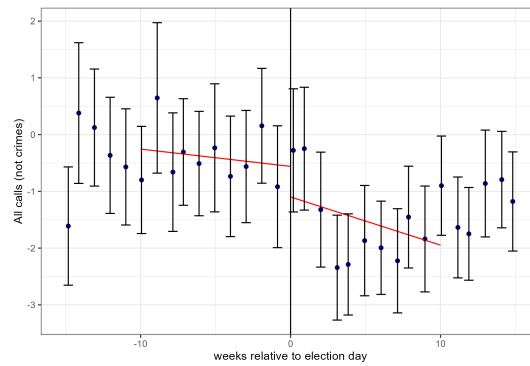


Figure 3. 911 Calls, weekly analysis

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), weekly analysis

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.

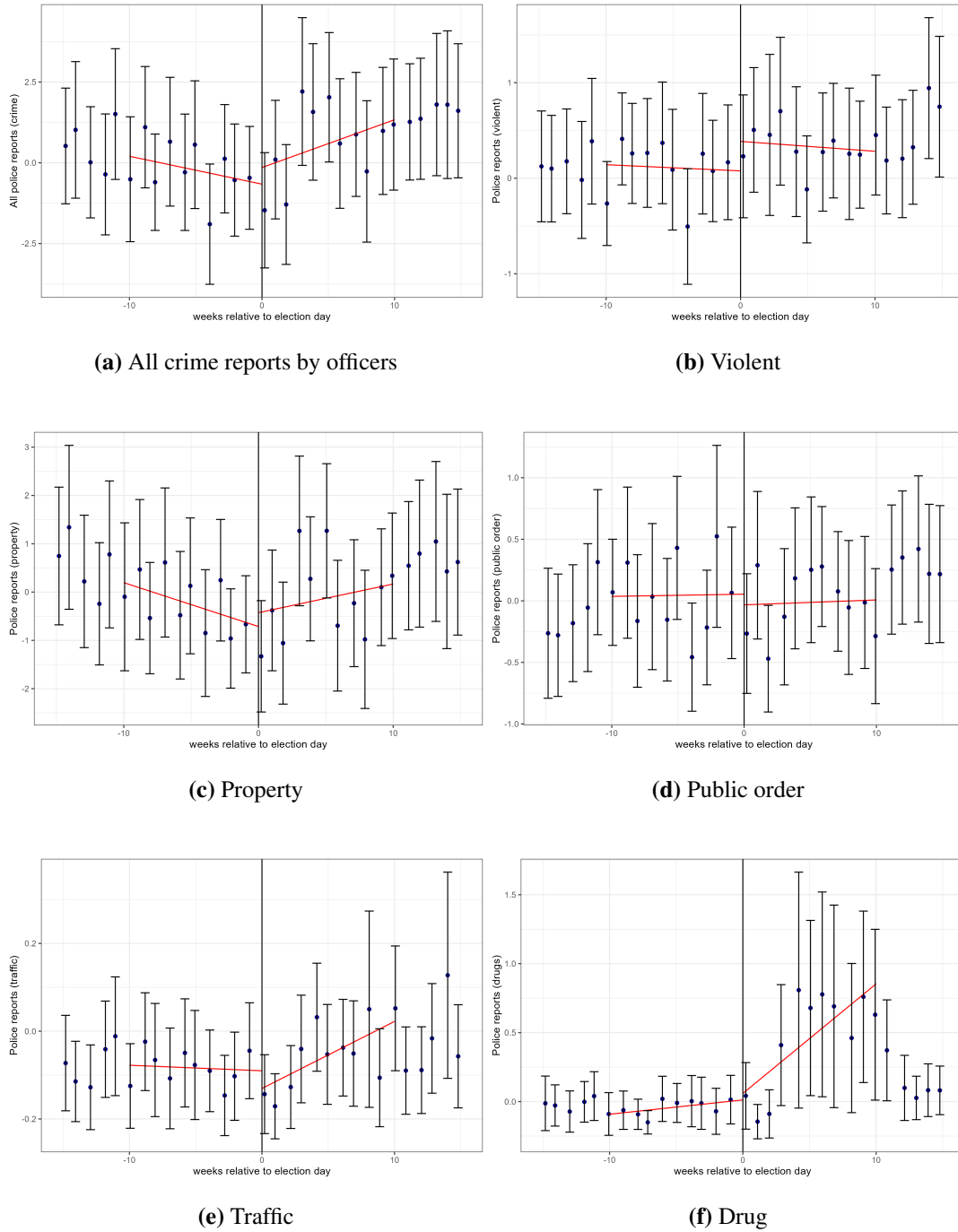
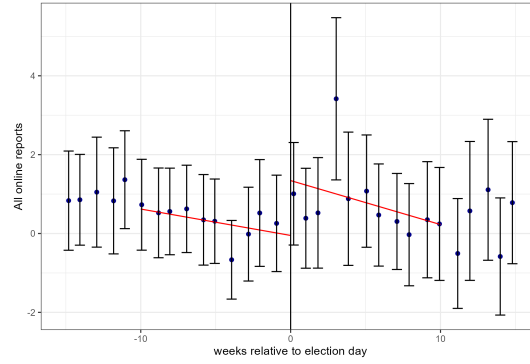
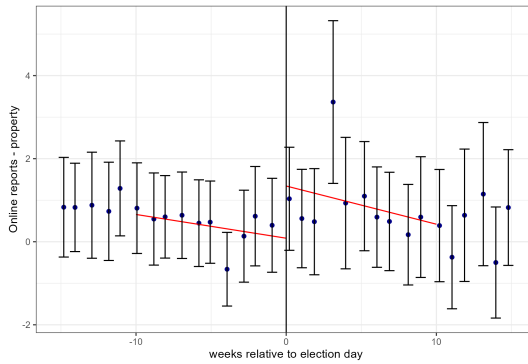


Figure 5. Reports filled by officers, weekly analysis

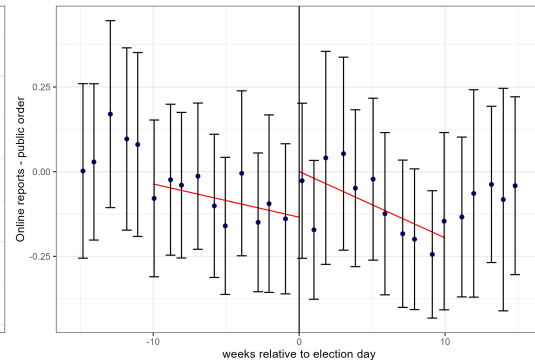
Note: Daily police reports data, 2022. The vertical line marks the recall election date (June 7th). Generated using the `rdplot` function in R's `rdrobust` package. The function uses the mimicking variance evenly-spaced method (`esmv`) to select the number of bins for the running variable (weeks relative 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



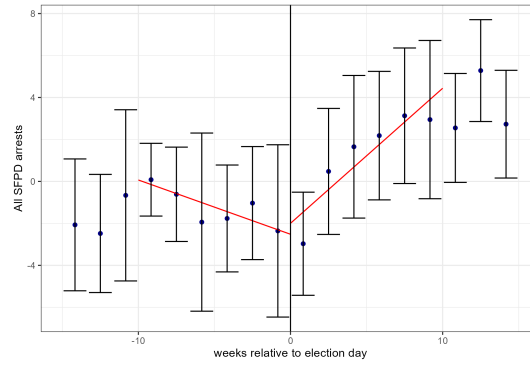
(b) Property



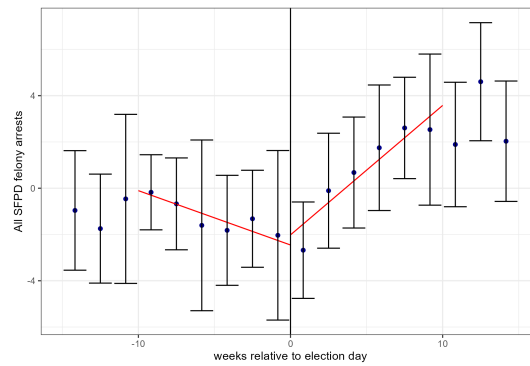
(c) Public order

Figure 6. Reports filled online, weekly analysis

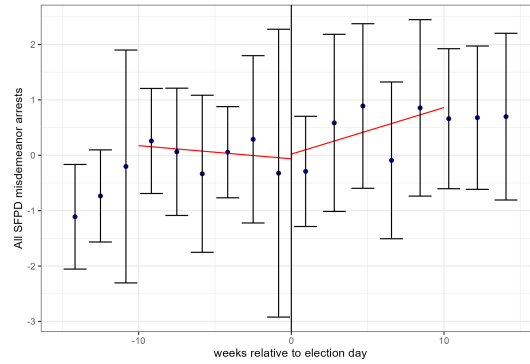
Note: Daily citizen reports data from 2022. The vertical line marks the recall election date (June 7th). Generated using the `rdplot` function in R's `rdrobust` package. The function uses the mimicking variance evenly-spaced method (`esmv`) to select the number of bins for the running variable (weeks 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) Felony arrests of SFPD



(c) Misdemeanor arrests of SFPD

Figure 7. Arrests, weekly analysis

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.

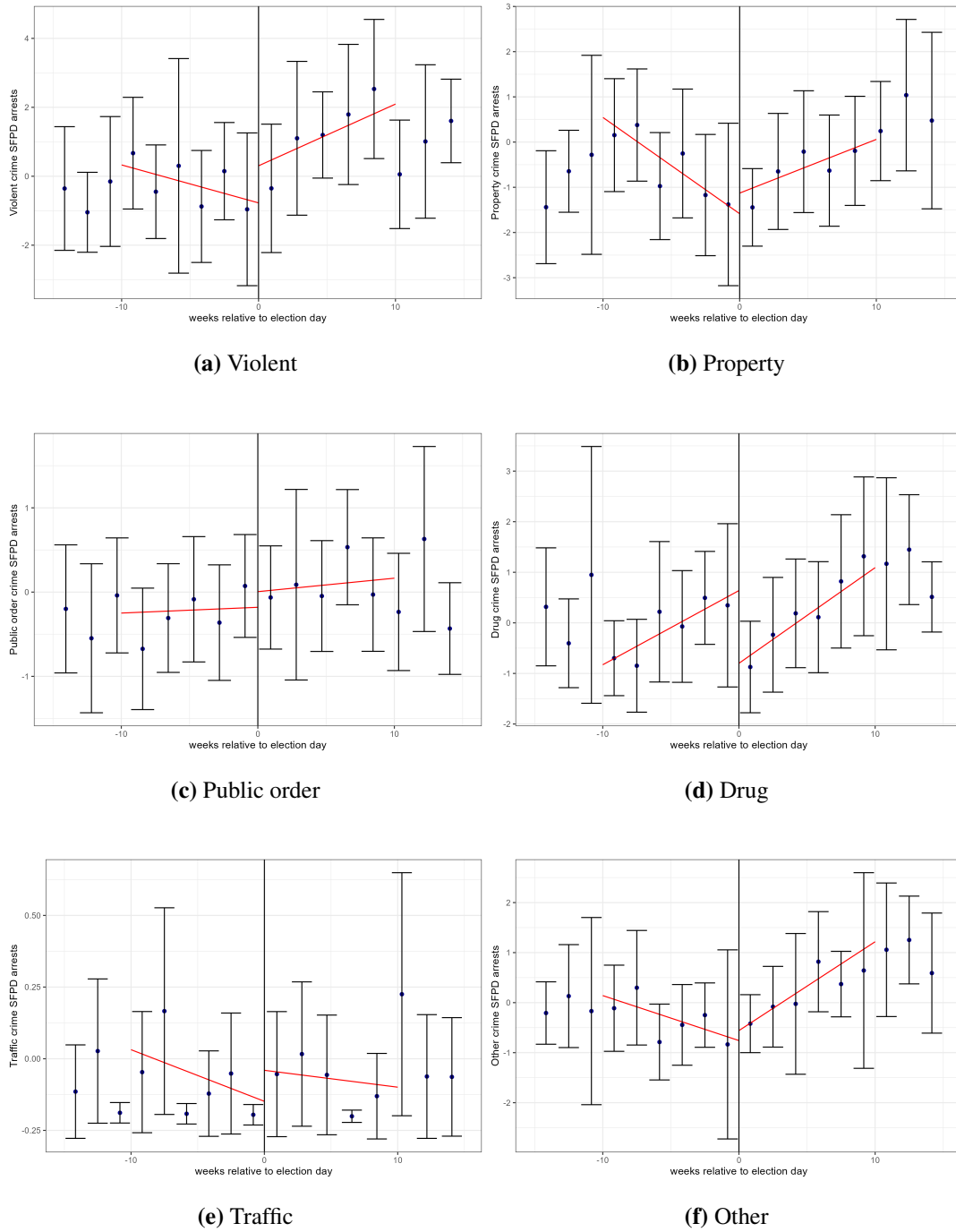
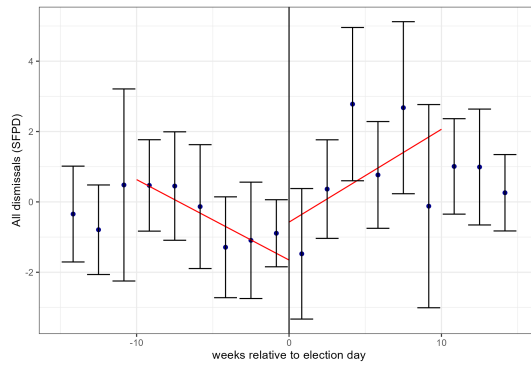
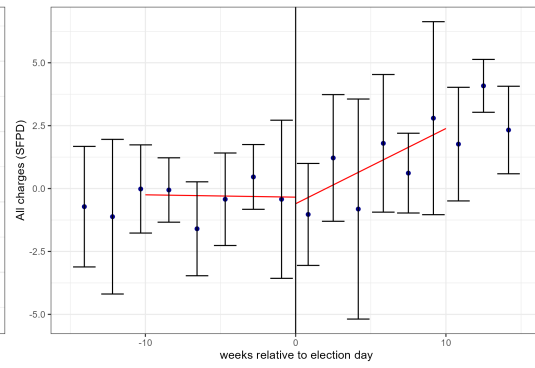


Figure 8. Arrests of SFPD by types of crimes, weekly analysis

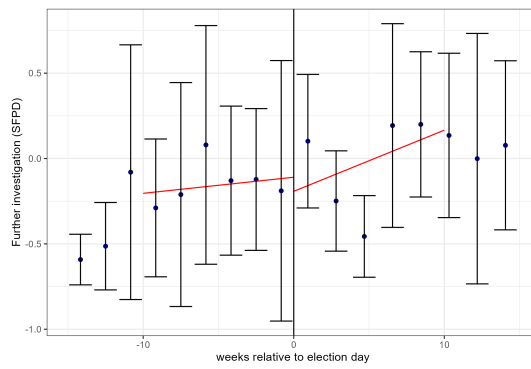
Note: Daily SFPD arrest data from 2022. The vertical line marks the recall election date (June 7th). Generated using the `rdplot` function in R's `rdrobust` package. The function uses the mimicking variance evenly-spaced method (`esmv`) to select the number of bins for the running variable (weeks relative 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.



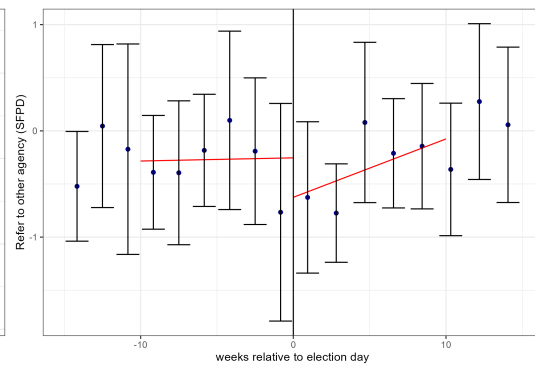
(a) Num of dismissals of SFPD arrests



(b) Num of charges of SFPD arrests



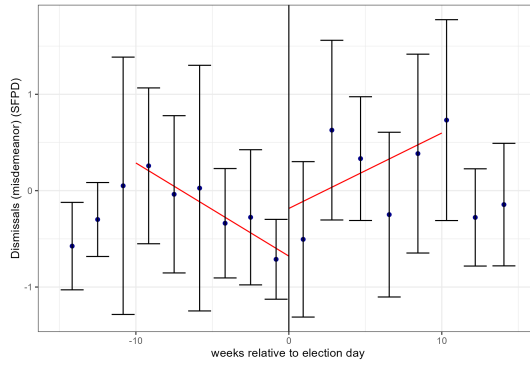
(c) Num of further investigation requested of SFPD arrests



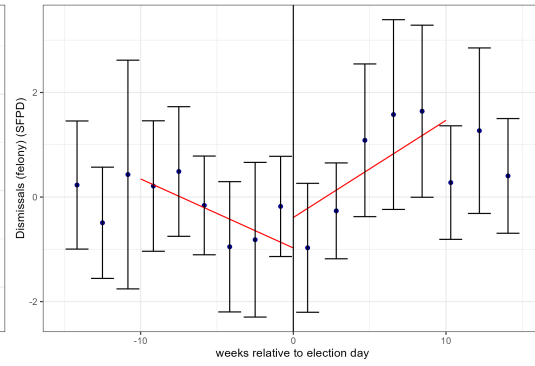
(d) Num of MTR/Referred to other agency of SFPD arrests

Figure 9. DA action of arrests, weekly analysis

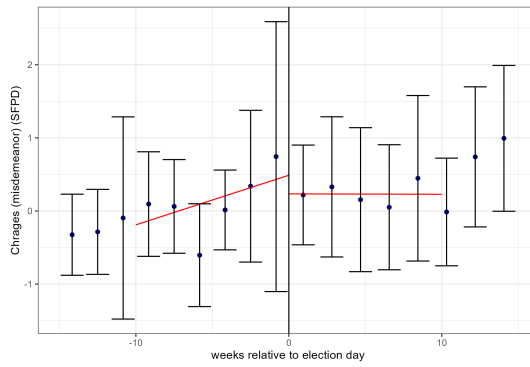
Note: Figure continued on the next page.



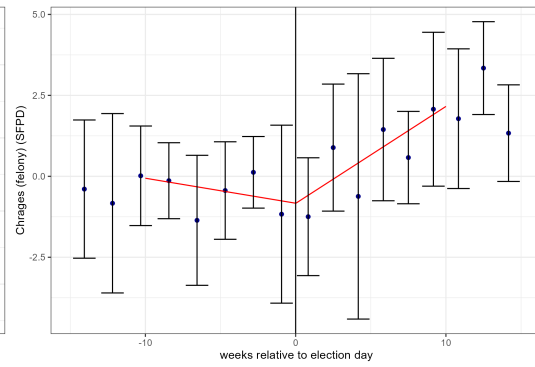
(e) Dismissals of misdemeanor SFPD arrests



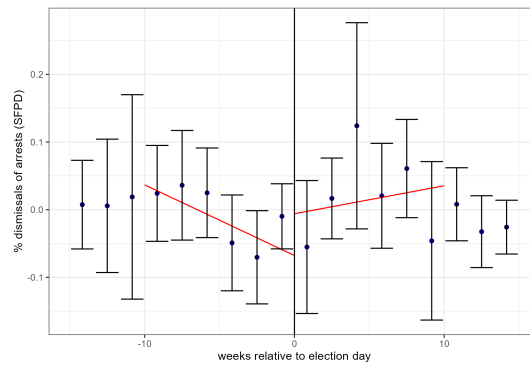
(f) Dismissals of felony SFPD arrests



(g) Charges of misdemeanor SFPD arrests



(h) Charges of felony SFPD arrests



(i) % dismissals of SFPD arrests

Figure 9. DA actions of arrests, weekly analysis

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.

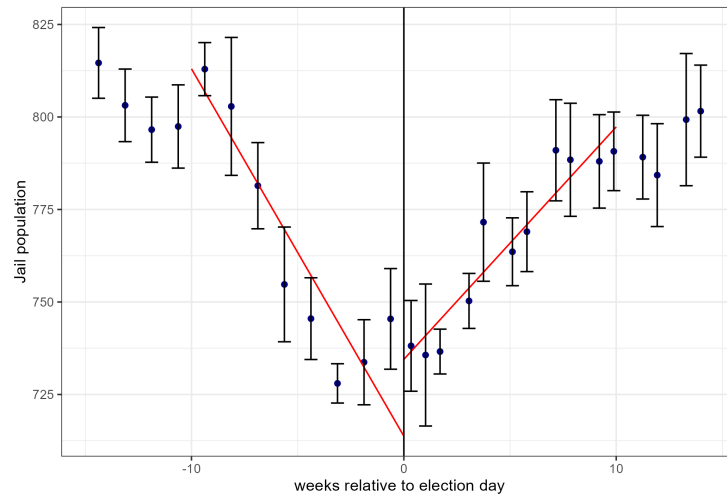


Figure 10. Daily jail population

Note: Daily jail population data from December 24th, 2021, until December 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.

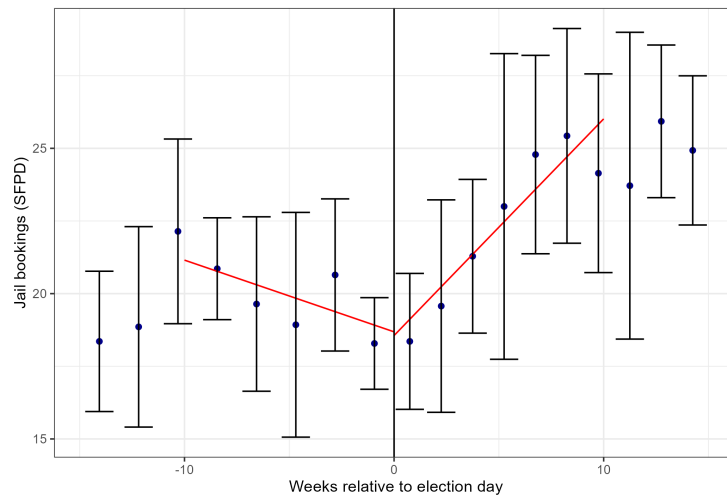


Figure 11. Jail bookings from SFPD

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.

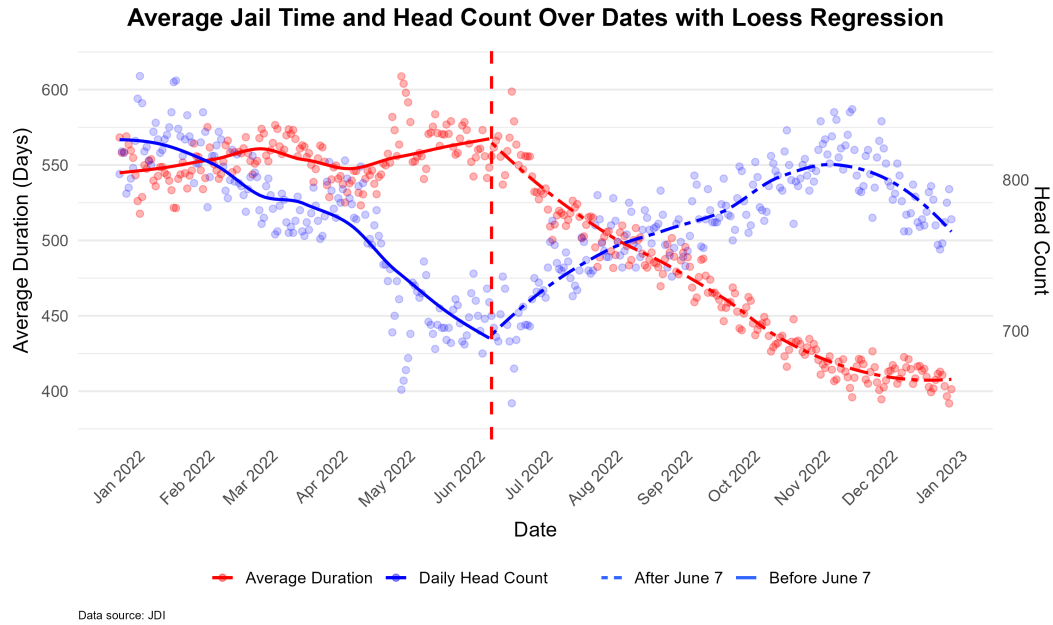


Figure 12. Average Jail Stay Duration

Note: This figure shows in red the average duration in days of all the people in the San Francisco jail on a given day with a Loess-fitted line. In blue, the figure shows the jail population.

9 APPENDIX

9.1 BW Sensitivity

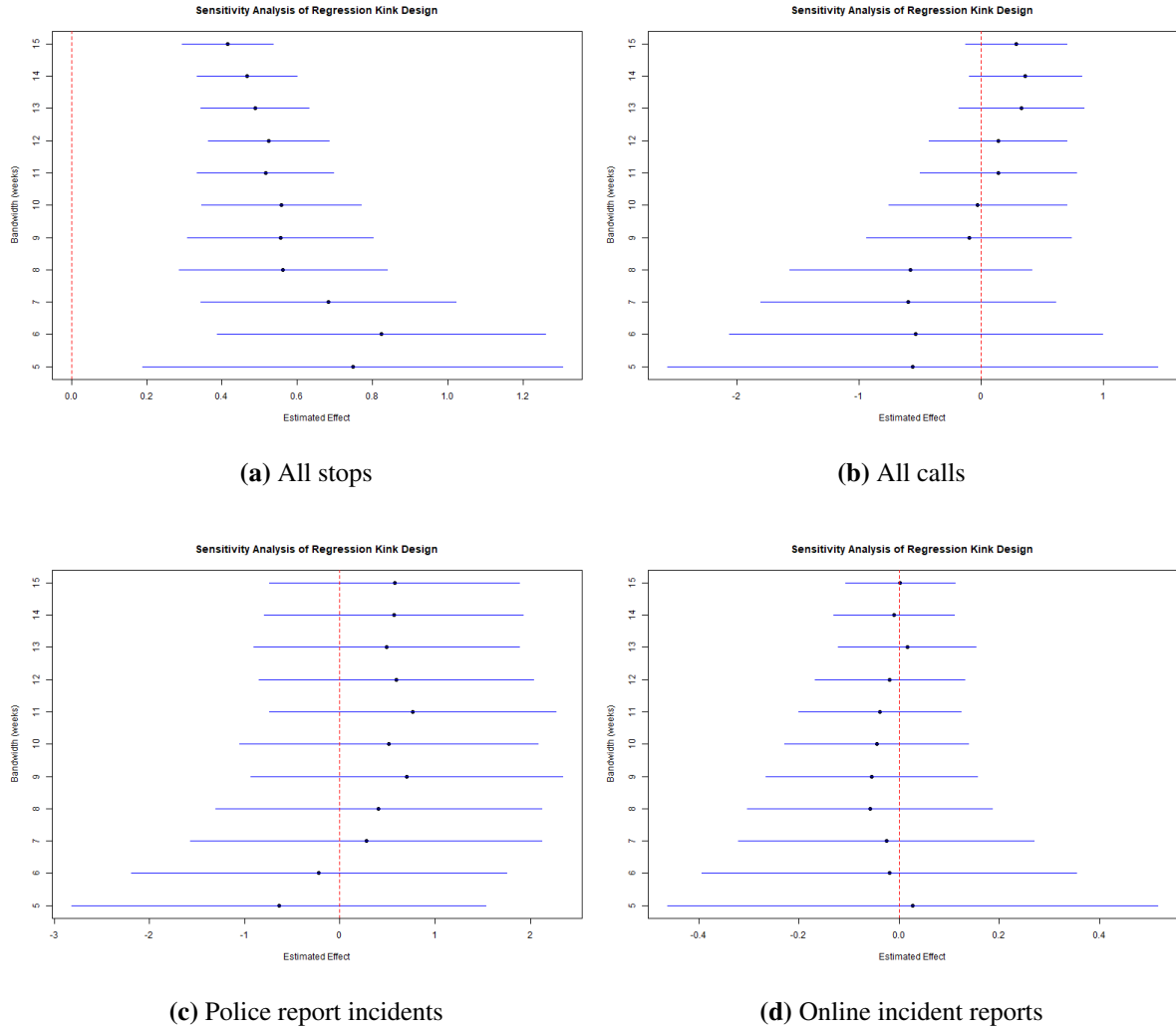
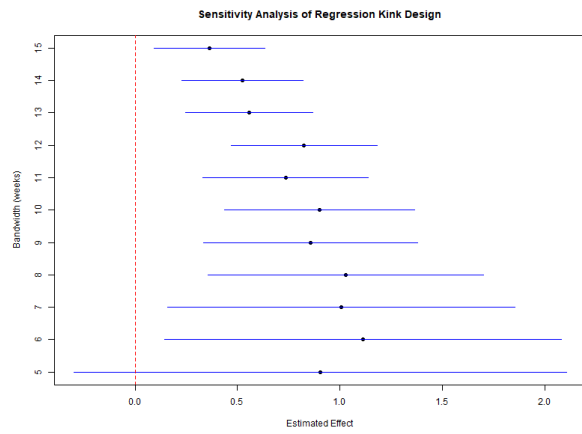
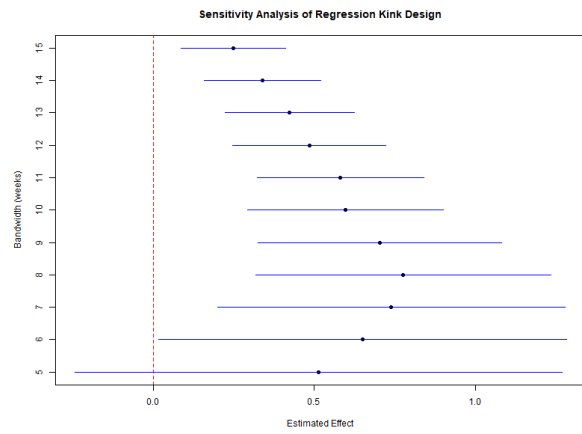


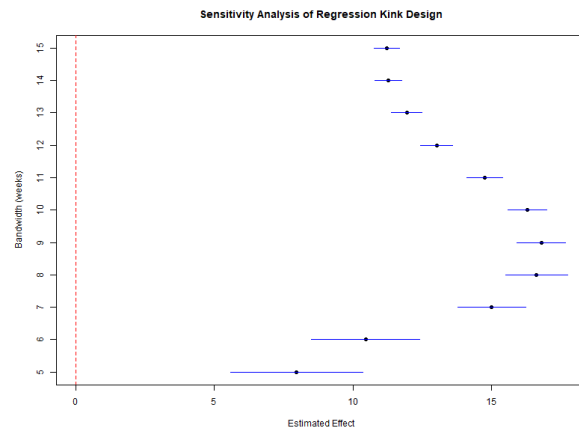
Figure 13. BW sensitivity analysis, Part 1



(e) All arrests of SFPD



(f) SFDA total dismissals



(g) Jail population

Figure 13. BW sensitivity analysis, Part 2

Table 9. Placebo test - 2021 data

Outcome	Recall election			June 7, 2021 Placebo		
	Slope change	Trend pre	Trend post	Slope change	Trend pre	Trend post
Police Behavior						
Police stops						
All Stops (crimes only)	0.558***	-	+	3.72*	-	NA
Police reports						
All Incident Reports (crime)	0.234	-	+	-3.018***	+	-
Police arrests (SFPD)						
All arrests	0.902***	-	+	0.117	NA	NA
All felony arrests	0.794***	-	+	0.129	NA	NA
All misdemeanor arrests	0.107	-	+	-0.011	NA	NA
Residents Behavior						
Residents Calls						
Crime related	-0.027	-	-	-5.21**	+	-
Non-crime related	-0.054	-	-	-0.939	NA	NA
Residents Online Reports						
All residents' online reports	-0.045	-	-	-4.258***	+	-
DA Behavior						
All charges	0.308	+	+	0.094	NA	NA
All dismissals	0.492***	-	+	-0.073	NA	NA
Charges (felony)	0.376*	-	+	0.188	NA	NA
Charges (misdemeanor)	-0.068	+	+	-0.093	NA	NA
Dismissals (felony)	0.317**	-	+	-0.109	NA	NA
Dismissals (misdemeanor)	0.174*	-	+	0.035	NA	NA
Jail Population						
Population	16.276***	-	+			
Bookings (all)	1.068***	-	+			
Bookings (SFPD)	0.991***	-	+	-0.068	NA	NA

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