Exposure to Police Violence, Service Protection and Voter Support for Defunding the Police

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Abstract

Following the 2020 George Floyd protests, calls to "defund the police" were common and subjected to popular vote in subnational jurisdictions in the United States. These proposals were advanced as a means of redressing excessive force in policing but were met with opposition on the grounds of concern over maintaining the service capacity of law enforcement agencies. Focusing on a ballot measure in Los Angeles County proposing to divert funding away from the largest county-level law enforcement agency in the nation, we explore the roles of service protection and exposure to lethal police violence as potential factors shaping the vote. We find that support for the measure was lower among voters facing the risk of diminished service capacity and that exposure to lethal police violence increased support for the measure—but only among voters under the jurisdiction of a municipal police department whose funding would not be affected.

Word Count: 11501

Introduction

The police killing of George Floyd on May 2020 in Minneapolis triggered the largest episode of social protest in American history (Buchanan and Patel, 2020). A major protest slogan that emerged during the Floyd protests was "defund the police" (Miller, 2020), which alludes to divesting public funds from law enforcement agencies (LEAs) and reallocating them to non-policing forms of public safety and community support (BLM Global Network, 2020; Lowrey, 2020; Ray, 2020). In the aftermath of the Floyd protests, elected officials in cities throughout the United States vowed to reduce the funding and operations of municipal police departments (Levin, 2020). Since then, over a dozen major American cities reduced their police budgets in 2021 (Akinnibi et al., 2020) and emerging evidence indicates that the largest cuts occurred in cities that experienced the most intense protests during summer of 2020 (Ferrer and Nguy, 2020).

Calls to defund the police (DTP) have moved beyond the street and town hall meetings and onto local ballots, with the seminal case being Measure J in Los Angeles County in the November 2020 General Election. This ballot measure proposed diverting a minimum of 10% of the county budget (estimated to be $36.2 billion in FY 2021-22[1]) away from the Los Angeles County Sheriff's Department, the largest county-level LEA in the nation, and investing the funds into community-based social services and restorative justice programs. Measure J passed with 57% of the vote, and was followed by defunding initiatives subjected to popular vote in the Chicago suburb of Oak Park in April 2021 and the city of Minneapolis in November 2021. Following the rise of the DTP movement during the 2020 Floyd protests, over a dozen polls conducted by major survey organizations and research foundations have asked about Americans' support for DTP,[2] indicating strong interest in understanding public support for police defunding as a type of progressive justice reform.

[1] `https://lacounty.gov/budget/`

[2] According to Roper iPoll, there were no surveys asking about "defunding the police" prior to the 2020 BLM protests. After, several polls conducted by Pew, USA Today, Axios, PRRI, Monmouth University, Marquette Law, and ABC News, asked the public concerning their support for and interpretation of "defund the police."

What shapes public support for DTP initiatives? A central feature of DTP that sets it apart from other popular post-Ferguson police reforms (e.g., bias training, body cameras, and civilian oversight) is the explicit trade-off presented to the public by competing policy stakeholders between (a) redressing excessive force in policing and (b) maintaining the capacity of LEAs to provide public safety. Proponents of DTP argue that violence against people of color is deeply ingrained in policing in America and that the solution is to curtail the operations of LEAs and pursue crime prevention with spending on social programs (BLM Global Network, 2020; Lowrey, 2020; Ray, 2020). Opponents of DTP contend that society *needs* the police and that decreased funding could result in reduced deterrence and elevated crime (Helfgott, 2020). Moreover, given the prevalence of calls for police service in high-crime non-White neighborhoods (Miller, 2020) and majority support among Black Americans for maintaining the level of police presence in their community (Saad, 2020), some opponents of DTP cast them as potentially exacerbating existing racial inequities (Rantz, 2021).

In this article, we explore the sources of public support for police defunding using the case of Measure J in Los Angeles County (LAC). Within the scholarly literature, there exists a widening vein of studies focused on the deleterious effects of contact with the carceral state (Weaver and Lerman, 2010; Bor et al., 2018a; Legewie and Fagan, 2019; White, 2019a; Ang, 2021). However, the growth of the Black Lives Matter movement and progressive justice reform organizations has yielded heightened opportunities for citizens to pushback against the carceral state. As such, a small but growing second vein of research within the literature builds on long-standing work on the repression-mobilization nexus (Davenport et al., 2005; Carey, 2006) to explore how exposure to carceral institutions may mobilize citizens into political action aimed at retrenching the carceral state (Drakulich et al., 2017; Laniyonu, 2019; Walker, 2014). We extend this latter work to Measure J in LAC, giving particular attention to how exposure to a salient feature of the carceral state—the enactment of lethal violence by the police—affected voter support for the initiative.

DTP initiatives represent complex proposals when it comes to the potential sources of voter preference formation by pitting motives for carceral state retrenchment against a key form of self-interest: the availability of police service if or when needed. Our analysis incorporates the potential countervailing motive of service protection by taking advantage of a unique feature of Measure J: it was directed against funding for the Los Angeles County Sheriff's Department (LASD) but would not affect the budgets of the 46 municipal police departments (MPDs) in operation in LAC. Thus, Measure J confronted voters in LAC with a distinct proposal depending on where they lived: for voters under the jurisdiction of the LASD, it involved defunding the policing agency servicing one's own household and neighborhood; however, for voters under the jurisdiction of a MPD, it involved defunding a widely-known locally-operating LEA while leaving the budget of the police agency servicing one's own household and neighborhood untouched. This feature of the vote implies the presence of a self-interest-based service-protection motive for voters under the jurisdiction of the LASD while the absence of such for those under that of a MPD.

Drawing on administrative election results data, we analyze voter support for Measure J among 3,019 election precincts in LAC. We combine this data with information about the jurisdictional boundaries for the LASD and MPDs and the location and timing of police killings of civilians in LAC. Our analysis begins with model-based approaches exploring precinct-level Measure J support by LEA jurisdiction as well as by proximity to police killings of civilians. We complement these with more rigorous design-based approaches that greatly reduce observed covariate imbalances between compared precincts. These design-based approaches subset the data to include only neighboring precincts strewn along different sides of LASD jurisdictional boundaries or precincts extremely close to police killings that vary in whether the killing occurred shortly before versus after the 2020 Election. We uncover evidence of service protection in the form of lower support for Measure J in precincts under the jurisdiction of the LASD compared to a MPD. Finally, while we find that exposure to police killings of civilians is associated with greater support for Measure J, this relationship only materializes among precinct voters under the jurisdiction of a MPD. This latter finding suggests that, to the extent that exposure to lethal police violence provokes a desire to curtail the police, voters seemingly only follow through in doing so when it comes at little presumed cost in future police services for one's household or neighborhood.

The Carceral State and Voter Support for Police Defunding

Research on the "carceral state" (Gottschalk, 2008; Weaver and Lerman, 2010) argues that contact with carceral institutions is politically demobilizing—it erodes trust in government and leads to a withdrawal from civic and political life. A growing body of evidence focusing on the relationships between arrest and/or incarceration and political trust and engagement supports this prediction (Hjalmarsson and Lopez, 2010; Weaver and Lerman, 2010; Burch, 2013; White, 2019a; White, 2019b). One facet of contact with the carceral state that is gaining scholarly attention is exposure to aggressive policing and police violence. This thread of research finds that exposure to policing programs involving the saturation of neighborhoods with officers engaged in constant investigative stops and frequent use-of-force reduces calls for government service (Lerman and Weaver, 2014b), turnout in elections (Laniyonu, 2019), educational attainment (Legewie and Fagan, 2019) and psychological well-being (Geller et al., 2014; Sewell et al., 2016).

An outcome of police-civilian interaction that perhaps most strongly conveys the state's "monopoly of violence" (Cohen et al., 2019, p. 1111) and "absolute power over citizens" (Weaver and Lerman, 2010, p. 818) is the police killing of civilians. Existing research finds that exposure to information about a police killing reduces trust in the police (Boudreau et al., 2019) and residential proximity to police killings has deleterious effects on school achievement and mental health (Bor et al., 2018a; Gershenson and Hayes, 2018; Ang, 2021). This research echoes the overarching carceral state literature by positing mechanisms including anger, fear of victimization by the police, the erosion of perceived procedural justice, and a conveyed discounting of worth and second-class social status to community members identifying with victims (Epp et al., 2014; Fagan et al., 2016). Together, these works have led to the accumulation of evidence of the damaging effects of personal and indirect exposure to a range of actions (e.g., investigative stops, arrest, incarceration, and lethal violence) yielded by the punitive face of government.

Complementing this body of work, however, is a small but growing vein of research exploring the possibility that exposure to carceral institutions may also spur pushback by citizens and efforts to retrench the carceral state (Drakulich et al., 2017; Laniyonu, 2019; Walker, 2020; Ang and Tebes, 2020). Historically, there are myriad instances of police violence instigating large-scale episodes of social protest (e.g., the Harlem Uprising of 1964, 1980 Miami Uprising, 1992 Los Angeles Uprising, and the 2014 Ferguson Uprising), which comports with long-standing theories on repression-mobilization (Davenport et al., 2005; Carey, 2006) contending that state repression and violence—often enacted by police forces—can trigger various types of oppositional activity once it surpasses a certain threshold. Building on these historical events and theories, recent scholarship has enabled the carceral state framework to offer a basis for expecting carceral contact to mobilize political action by focusing on the complementary concepts of proximal contact and policy threat. Proximal contact is defined as indirect exposure to carceral institutions (e.g., the police, courts, and prison) through family members or residing in communities that are heavily policed or impacted by other criminal justice interventions (Walker, 2014). Policy threat refers to the potential for policies that are harmful to a specific group to activate group consciousness and solidarity and engender political action in resistance to threatening policies (Campbell, 2003; Pantoja and Segura, 2003; Cho et al., 2006).

Tying these concepts together, scholarship in this vein of research theorizes that individuals with proximal contact have two key ingredients for reactionary political action against the carceral state: (a) the motivation to participate, and (b) the possession of more participation-facilitating resources (e.g., political efficacy and the ability to vote) relative to custodial citizens. This expectation is supported by evidence presented by Walker (2014) indicating that, while personal carceral contact is associated with decreased voter turnout, proximal contact is associated with increased engagement in various forms of participation beyond voting. Adding to this, Laniyonu (2019) finds that residing in heavily-policed neighborhoods is associated with increased voter turnout in local elections featuring candidates advocating for police reform but associated with depressed turnout in elections where police reform was not a focal issue. Focusing specifically on police violence, Williamson et al. (2018) find that Black Lives Matter protests between 2014-2015 were more likely to occur in localities where more Black people had been killed by the police, and Ang and Tebes (2020) find that residing very close to the site of police killings of civilians leads to increases in voter turnout and support for criminal justice reform.

Applied to the case of DTP, this work suggests that proximal contact with the carceral state—particularly in the form of exposure to lethal police violence—may serve as a source of public support for police defunding. The DTP movement emerged in response to the police killing of George Floyd and the focus on redressing excessive police violence in DTP initiatives may resonate with voters exposed to the police killing of civilians. Existing research finds that public trust in the police drops in response to the police killing of civilians (Drake, 2014; Boudreau et al., 2019) and that political distrust reduces support for government spending (Chanley et al., 2000; Hetherington, 2018) and heightens support for policy initiatives that withdraw funds from government (Sears and Citrin, 1982). A logical extension of these findings is that exposure to police killings may engender support for withdrawing funding from the police. Applied to an initiative to DTP, this work provides a foundation for the expectation that support for the initiative will be greater among voters exposed to police killings of civilians (*police violence hypothesis*). This expectation is consistent with scholarship on the mobilizing potential of carceral contact and research analyzing the repercussions of exposure to lethal police violence.

Initiatives to DTP, however, potentially pit the desire to curtail police violence against concern over the availability of police service. Arguments against DTP are replete with assertions of the indispensable nature of the police and the contention that reducing funding to LEAs will diminish their capacity to respond to calls for service when people need the police (National Police Support Fund, 2021). Some arguments against DTP *concede* that police reform is needed in order to address excessive force in policing, but contend that DTP is the wrong approach to doing so because it puts public safety in jeopardy (Helfgott, 2020). With these arguments in mind, when presented with a concrete policy initiative that would reduce funding for citizens' own local LEA, a form of self-interest may emerge centering around *service protection*—the motive to protect the capacity of one's own LEA to provide service to one's household if or when needed. Scholarship working within the carceral state framework draws on the concept of policy threat to argue that criminal justice practices may mobilize to action those whom they directly or indirectly harm (Laniyonu, 2019; Walker, 2020). This concept, however, is also applicable to proposals to defund citizens' own LEA, as they evoke the threat of a policy change that could lead to salient perceived harms (e.g., reduced service and public safety). Given that such threats are highly catalyzing of political action (Miller and Krosnick, 2004), it is reasonable to expect that self-interest in the form of service protection would be an operative factor depressing voter support for an initiative to defund their own LEA (*service protection hypothesis*). Moreover, one further implication of the desire for service protection is that it may serve as a countervailing force to the motive for carceral state retrenchment following exposure to police killings of civilians.

The Case of Measure J in Los Angeles County

On the November 3rd, 2020 General Election, voters in Los Angeles County (LAC) were presented with Measure J, a county-wide ballot initiative soliciting a "Yes" or "No" vote on a proposed county charter amendment that would require LAC to divert 10% of its discretionary budget away from "carceral systems and law enforcement" in order to be spent on social

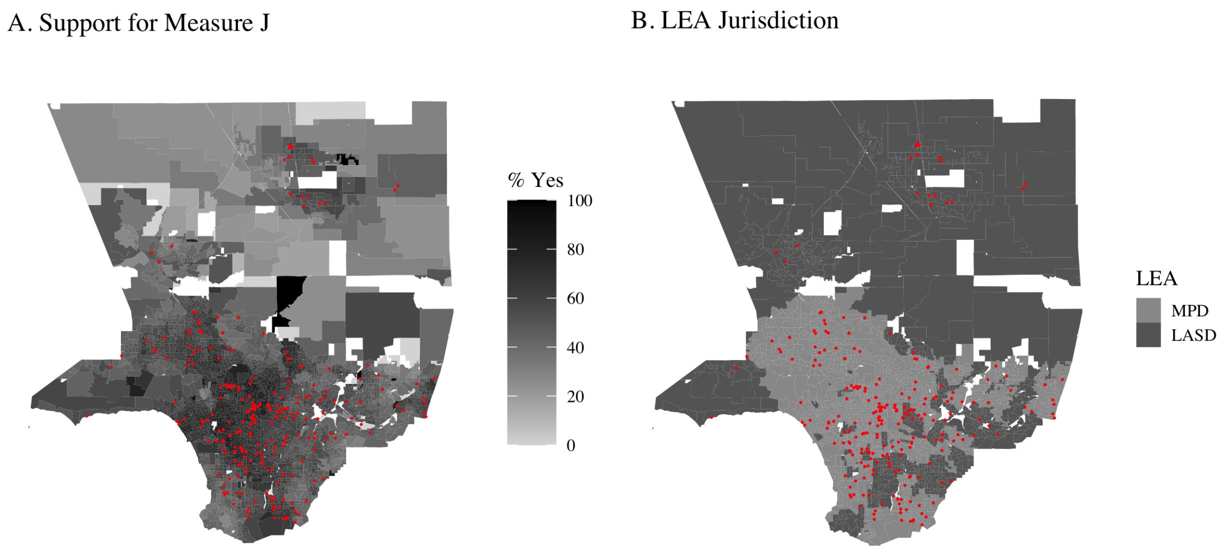

Figure 1: Map of LAC with Election Precinct Boundaries. Maps depict precinct support for Measure J (Panel A) and LEA jurisdiction (Panel B). Red dots in both panels indicate the location of police killings of civilians in the 4 years prior to the November 3, 2020 election. White spaces are precincts with 0 overall votes or 0 votes on Measure J.

services and jail diversion. The earmarked funds under the proposed charter amendment explicitly prohibited the funds from being used on prisons, jails, or the Los Angeles County Sheriff's Department (LASD). The principal group behind Measure J was a coalition of local organizations, including the Long Beach and Los Angeles chapters of Black Lives Matter, working under the name "Re-imagine Los Angeles," who publicly characterized it as a "ballot measure to divest from incarceration and policing and invest in the health and economic wellness of marginalized people in their communities."[3] Measure J passed with 57% of the roughly 3.8 million votes cast throughout LAC. Figure 1, Panel A provides a greyscale heatmap of voter support for Measure J in LAC election precincts, revealing greater support in Central LA, the South Bay and Gateway and Westside Cities relative to Santa Clarita and the San Fernando, Antelope, and San Gabriel Valley subregions.

Measure J is a suitable case for studying voter support for DTP for several reasons. First, central characteristics of Measure J as a defunding proposal fit the American public's

[3]See `https://reimagine.la/about/`

understanding of the moniker "defund the police." A survey conducted in 2020 found that 70% of Americans perceived the protest slogan "defund the police" to mean "redirect some police department funding to other social services" as opposed to "eliminating police departments completely."[4] Second, the initiative was put to a vote, enabling researchers to observe revealed preferences as compared to reported attitudes—which is valuable given that reported attitudes do not always align with future behavior (LaPiere, 1934). Third, various sources of information available to voters made it clear that Measure J was a defunding initiative; moreover, these sources of information also made it clear that the measure would only affect the LASD as compared to the 46 MPDs operating within LAC.[5]

First and foremost, all voters in LAC were sent sample ballots and voter information guides that provided ballot wording and arguments in favor and against each measure (see Appendix A). These materials explicitly told voters that the funds set aside from Measure J *could not* be used for the LASD, and no other LEA was singled out in these materials. The official arguments appearing against Measure J told voters that it "permanently takes $500,000,000 in funding away" from "911 operators" and "public safety officers." Second, local media coverage and media outreach by prominent stakeholders in the county explicitly depicted the initiative as a defunding measure targeting the LASD. Discussion of Measure J appearing in the *Los Angeles Times* made it clear the measure implicated the budget of the LASD and that its principal opponent was the LASD (Cosgrove, 2020). Opponents of Measure J publicly argued that it was a de facto DTP policy since money would inevitably be reduced from the LASD to fund social programs mandated by the charter amendment. For example, the Sheriff of the LASD, Alex Villanueva, publicly characterized Measure J as a "campaign to continue defunding LASD" that would make the streets of LA "look like a scene from Mad Max."[6] Additionally, the LASD released a statement on its website

[4]PRRI 2020 American Values Survey, Question 92, 31118163.00091, PRRI, (Cornell University, Ithaca, NY: Roper Center for Public Opinion Research, 2020)

[5]http://www.laalmanac.com/crime/cr69.php

[6]See `https://twitter.com/LACoSheriff/status/1285718712243412992`

claiming the measure would mean “additional reductions to our budget.”[7] The Association for Los Angeles Deputy Sheriffs alone spent $3.5 million on TV and social media advertising indicting Measure J’s purported threat to public safety by constraining the pool of resources for law enforcement.[8] In the end, the primary opponents on record for Measure J were Sheriff Villanueva and the Association for Los Angeles Deputies,[9] which is the union comprised of LASD officers. Critically, no officials or associations for any MPDs operating within LAC officially opposed the measure. Finally, evidence that voters in LAC perceived Measure J as a police defunding initiative comes from internet search activity and social media commentary in the LA metro area in the weeks before and after the 2020 Election. Time-stamped and geocoded data from Google Trends and Twitter reveal that internet searches for and Tweets containing “Defund the police” by internet users in the LA metro area spiked leading up to and following the 2020 Election (Figure B9).

In addition to offering a fitting case for studying voter support for DTP, the case of Measure J offers a unique opportunity to assess the operation of self-interest in the form of service protection due to the county-wide nature of the vote but the disparate intra-country organization of LEA jurisdiction in LAC. Critically, election precincts in LAC are either serviced by the LASD or a MPD, with no overlap in LEA jurisdiction. Figure 1, Panel B, depicts the jurisdictional boundaries of the LASD, showing the election precincts serviced by either the LASD (dark grey) or a MPD (light grey). Given Measure J only implicated the county budget and the LASD, the initiative presented voters with the same ballot question but a qualitatively distinct choice depending on their LEA jurisdiction: voters residing in LASD-served precincts were presumably confronted with a trade-off between issuing a strike against local carceral institutions and preserving the service capacity of their own policing agency; whereas voters residing in MPD-served precincts were presented with an opportunity to issue a strike against local carceral institutions, but to do so in a manner that conveyed

[7] `https://lasd.org/statement-regarding-measure-j/`

[8] https://www.vox.com/2020/11/4/21549019/measure-j-police-abolition-defund-reform-black-lives-matter-protest-2020-election-george-floyd

[9] See the Ballotpedia page for Measure J and the official endorsements for the measure.

no implications for the service capacity of the policing agency covering their household. If popular arguments against DTP evoking concern over police service capacity have traction, such arguments should have been more salient to voters under LASD jurisdiction. While it is conceivable that voters served by a MPD could have been motivated by sociotropic concern over public safety in neighboring and remote county areas under LASD jurisdiction, their level of egotropic concern should have been little to none given that personally envisioning the need to call the police for their household would not entail calling the LASD. Therefore, consistent with the service protection hypothesis, we expect average support for Measure J to be lower among voters under the jurisdiction of the LASD. Additionally, concern over service protection may have served as a countervailing factor to exposure to police violence, thus attenuating its effect among voters residing in precincts serviced by the LASD.

Finally, LAC offers a valuable geographic context for our study for several reasons. First, LAC is the largest county in the U.S. by population, with over 10 million residents and 6 million eligible voters as of 2020, which renders it larger than 40 of the 50 U.S. states. LAC is demographically diverse, with large Latinx (48%), Asian (15%), and Black (8%) populations, and it contains 88 cities and approximately 140 unincorporated areas with a heterogenous set of characteristics along demographic, socioeconomic, and political dimensions. In addition, the LASD is the largest county sheriff's department in the U.S., with 18,000 employees, 10,000 sworn deputies, and service provision to 42 cities and 153 unincorporated LAC communities. Perhaps most relevant, LAC experiences the highest level of fatal police violence, with 708 police killings of civilians since 2010.[10] The maps in Figure 1 depict the spatial distribution of police killings in the county. LAC is an epicenter for research on the politics of police violence, as the county experienced two of the largest episodes of civil unrest in response to police violence: the 1965 Watts Rebellion and the 1992 Los Angeles Uprising. Applied to the case of Measure J, the police violence hypothesis renders the expectation that exposure to police killings of civilians served as a source of voter support for the initiative.

[10]Figure based on the Fatal Encounters database (downloaded May 21, 2021, see https://fatalencounters.org/)

Overview of Data and Methods

Our analysis uses administrative election results data for LAC from the November 3rd, 2020 General Election. We obtained this data at the smallest level of geographic aggregation available—the precinct-level—from the office of the LAC Registrar-Reporter/County Clerk.[11] In total, the final vote for Measure J was tabulated and reported for 3,019 election precincts.[12] The outcome variable in our analysis is the proportion of voters in each precinct casting a vote on Measure J who voted "Yes" on the initiative (*%Yes*, rescaled to range from 0 to 1).[13]

To determine if an election precinct is served by the LASD or a MPD, we retrieved data on service boundaries for all LEAs operating within LAC from the County of Los Angeles Open Data website.[14] We overlaid election precinct boundaries with LASD service boundaries in QGIS, and coded a precinct as served by the LASD if it was contained within LASD service boundaries. Conveniently, all precincts fall under the jurisdiction of a single LEA (LASD or a MPD) because both election precinct and LEA service boundaries are determined by the borders of cities and unincorporated communities throughout LAC.[15] We retrieved data on the police killing of civilians in LAC from the *Fatal Encounters* (FE) database (Finch et al., 2019), which has been used in leading research to describe the prevalence of police killings of civilians in the U.S. (Edwards et al., 2019), and to investigate the linkage between exposure to police violence and political protest (Williamson et al., 2018). The FE database includes information on the latitude/longitude coordinates of each killing, which we use to construct measures of precinct exposure to police killings. Importantly, we demonstrate in the appendix the robustness of results using the FE data to an alternative database on police killing of civilians compiled by the *Los Angeles Times*.

[11] See `https://www.lavote.net/home/voting-elections/current-elections/election-results/past-election-results`

[12] We exclude precincts with 0 votes overall or 0 votes on Measure J.

[13] Our analysis excludes abstainers from the denominator, but the findings do not change including them. Moreover, our independent variables of interest are not associated with abstention rates (Section C.12), suggesting abstention is not an operative factor in our analyses.

[14] `https://data.lacounty.gov/GIS-Data/Reporting-Districts/kvwy-dqs6`

[15] GIS data on LASD jurisdiction and LAC precinct boundaries were slightly jittered from each other, so we identified which precincts overlapped with LASD boundaries by hand.

Using these data, we employ *model-based* and more rigorous *design-based* approaches for testing each hypothesis. To test the service protection hypothesis, we utilize a model-based approach including all 3,019 precincts assessing whether or not there were average differences in support for Measure J between precinct voters served by the LASD versus a MPD. We complement this with a design-based approach that drastically reduces covariate imbalance between LASD and MPD precincts by analyzing the subset of neighboring election precincts strewn along different sides of LASD jurisdictional borders throughout LAC. To test the police violence hypothesis, we utilize a model-based approach including all precincts assessing whether or not support for Measure J differed between precincts far away from versus close to the site of a police killing. We complement this with a design-based approach that drastically reduces covariate imbalance between precincts far away from and close to a police killing by analyzing the subset of precincts very close to the site of a police killing (i.e., only "treated" precincts). This analysis compares Measure J support between precincts where the nearby killing occurred shortly before the 2020 election to those where the nearby killing occurred shortly after the election. While we do not position our design-based analyses as rendering causally identified estimates, we do view the substantial reduction in covariate imbalance brought by each design as increasing our confidence concerning estimated relationships between LEA jurisdiction or exposure to police killings and voter support for Measure J.

Service Protection and Measure J Support

Model-Based Approach

We begin by modelling precinct *%Yes* vote for Measure J as a function of LEA jurisdiction for all precincts in LAC. We created a dichotomous *LASD* variable coded '1' for election precincts under the jurisdiction of the LASD and '0' for those served by a MPD. Our analyses control for an extensive set of precinct-level covariates potentially correlated with LEA jurisdiction and support for progressive justice reform. Using census block group data from the 2015-2019

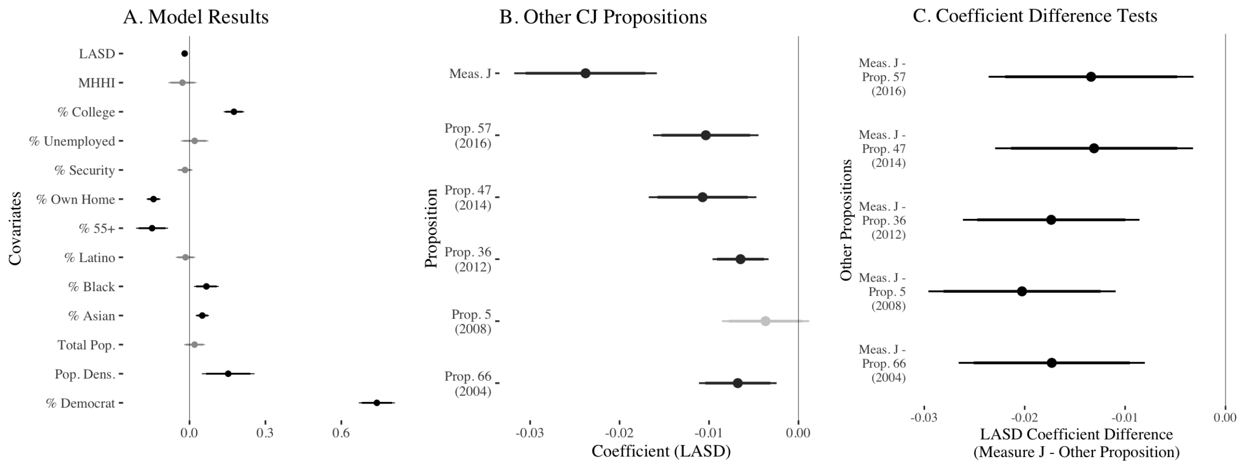

Figure 2: Model-Based Analysis of Service Protection and Support for Measure J. Panel A displays OLS coefficient estimates. Panel B displays OLS coefficient estimates for *LASD* variable on support for Measure J and five other criminal justice propositions using fully specified models. Panel C displays *LASD* coefficient difference estimates between Measure J and other criminal justice propositions, based on N=1,000 bootstrapped coefficient difference simulations. Statistically significant coefficients are black, insignificant coefficients are grey. 95% CIs displayed derived from robust HC2 SEs. All covariates rescaled between 0-1.

5-year American Community Survey, we use areal interpolation[16] to generate precinct-level estimates for population size and density, median household income, the percent of adults holding a college degree or higher, the percent of housing units that are owner-occupied, the percent of adults in the workforce that are unemployed, the percent of the population that is 55 years of age or older, the percent of the population that is either Black, Latinx or Asian, and the percent of adults employed in protective services (e.g., police and sheriff's officers). We also control for the percent of voters registered as Democrats.[17]

Figure 2, Panel A (Table C1), plots coefficient estimates from a model regressing precinct *%Yes* on LEA jurisdiction and covariates. Consistent with our service protection hypothesis, we find that, holding a range of factors constant, support for Measure J was roughly 2 percentage points lower (β=-0.019, p <0.001) among precincts served by the LASD. Given the possibility of a "suppression effect" in light of the 12 covariates in this model (Lenz

[16]Implemented via the `sf` package in $\mathbb{R}$.

[17]Retrieved from `https://statewidedatabase.org/d10/g16.html`. Given 2016 precinct boundaries slightly differ from 2020 precinct boundaries, we also use areal interpolation to generate estimates of the percent of precinct voters registered as Democrats in 2016 for 2020 electoral precincts.

and Sahn, 2021), we also estimated a bivariate model and find a statistically significant 11 percentage point decrease in Measure J support for LASD- relative to MPD-served precincts (Table C1). These results suggest trepidation about Measure J among precinct voters whose *own* household public safety provider was targeted by the Measure for funding reductions.

This result is robust to a series of checks. First, the results hold when using beta regression (Table C11). Second, one factor not accounted for with our controls is possible differences in the rigor of policing between the LASD and MPDs. If the LASD engaged in less rigorous routine policing than MPDs, it is conceivable this could engender greater amity toward law enforcement among LASD-served voters. Unfortunately, there is no publicly available administrative policing data for all of the LEAs operating in LAC. This said, we obtained publicly available time-stamped and geocoded police stop data for the two largest cites in LAC: Los Angeles and Long Beach, whose PDs have jurisdiction over N=1,217 precincts in the data. Additionally, the Sheriff's Automated Contact Reporting (SACR) system provides geocoded police stops data for the LASD, which has jurisdiction over N=982 precincts in the data.[18] We demonstrate in Table C7 that the intensity of routine policing, as captured by stops per capita, did not significantly differ between LASD-served precincts and those served by the LAPD or LBPD.[19]

Third, the estimated effect of *LASD* in Figure 2, Panel A, could be attributed to service protection, but could also be due to systematic differences in preferences over criminal justice policy having nothing to do with Measure J's targeting of the LASD. To further explore the role of service protection as a factor shaping the vote, we re-estimated the model underlying Figure 2, Panel A, using as dependent variables precinct *%Yes* vote on five ballot measures voted on by LAC voters between 2004 to 2016 that pertained to law enforcement and/or criminal justice but did not imply any funding reductions to the LASD (see Section C.2). If

[18]See Appendix Section C.3 for more details on police stop data throughout Los Angeles, Long Beach, and LASD-served precincts.

[19]Adjusting for stops per capita as an additional control covariate to evaluate the influence of LASD service provision on Measure J support in a truncated sample including LBPD, LAPD, and LASD precincts does not change the results (Table C3).

service protection drove the effect of *LASD* on Measure J, we should either (a) fail to observe similar negative effects on support for criminal justice initiatives not implicating LASD's funding, or (b) observe negative effects that are smaller in magnitude. Figure 2, Panel B, demonstrates that precincts served by the LASD are typically more conservative on criminal justice initiatives than those served by a MPD. However, the coefficient estimate for *LASD* for Measure J in Panel B is visibly larger than the estimates for the other initiatives. Critically, the results in Figure 2, Panel C indicate that the negative effect of *LASD* is significantly larger for Measure J than for the five other ballot initiatives, suggesting that—by uniquely evoking concerns over LASD service capacity—Measure J triggered opposition *above and beyond* what is typically observed among LASD-served precinct voters.

Design-Based Approach

Given the size of LAC and the concentration of LASD-served precincts in specific regions of the county, one concern is that LASD- and MPD-served precincts are significantly different on a host of characteristics. While our estimate for the *LASD* variable in the previous section adjusts for 12 covariates, we find considerable covariate imbalance between LASD- and MPD-served precincts (Figure 3, Panel B, see also Table D18). We find that precincts served by the LASD are significantly different than those served by a MPD on 11 out of 14 measured characteristics, including income levels, education rates, home ownership, racial demographics, population size and density, and partisanship. In short, the previous analysis compares drastically different precincts, rendering omitted variable bias a lingering concern.

To assess the robustness of our results, we employ a design-based approach that reduces covariate imbalance by restricting the analysis to the $N = 922$ neighboring precincts strewn along different sides of the LASD jurisdictional border throughout LAC (Figure 3, Panel A). As shown in Figure 3, Panel B, using this subset of precincts *drastically* reduces covariate imbalance between resulting LASD- and MPD-served precincts. Compared to the full sample of precincts, we only observe imbalance on 3 out of 14 variables, and for one of these, home

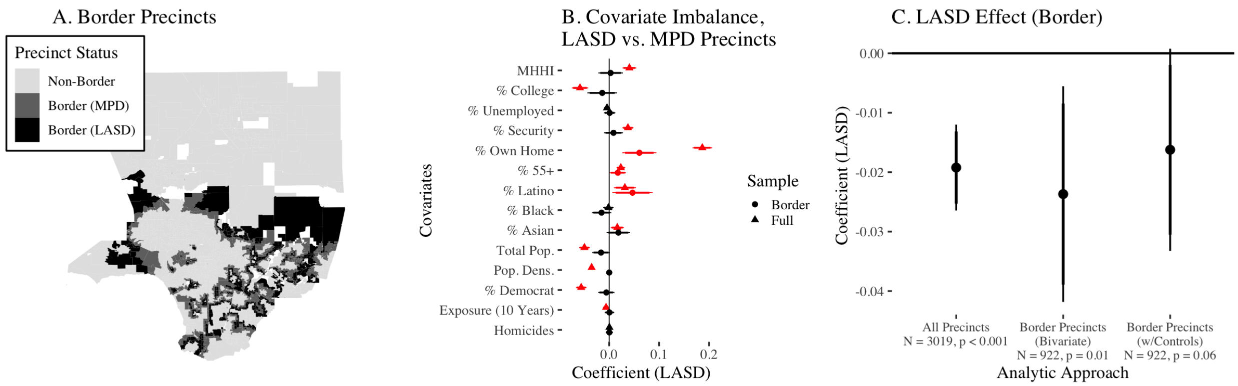

Figure 3: Design-Based Analysis of Service Protection and Support for Measure J Panel A is a map of LAC depicting neighboring LASD (black) and MPD (dark grey) precincts strewn along LASD jurisdictional borders (non-border precincts in light grey). Panel B displays a series of bivariate models assessing covariate balance between LASD and MPD precincts. Red coefficients are statistically significant, black coefficients are insignificant. Shape (circle or triangle) denotes whether the full or bordering precinct sample is used. Panel C displays coefficient estimates (y-axis) for *LASD* on support for Measure J using the full precinct sample (with controls) and the bordering precinct sample from a bivariate model and a model controlling for persisting imbalanced covariates (x-axis, from left to right). All covariates rescaled between 0-1. 95% CIs displayed derived from robust HC2 SEs.

ownership, the level of imbalance is significantly less in the bordering precinct than in the full sample. Using this subset of more demographically and politically alike precincts, we find that those under LASD jurisdiction were significantly less supportive of Measure J than contiguous precincts under the jurisdiction of a MPD in a bivariate model (β=-0.023, p < 0.01) and a model controlling for persisting imbalanced covariates (β=-0.016, p=0.061, Figure 3, Panel C, see also Table D19). The similarity between the estimates for the *LASD* variable retrieved from the model analyzing all precincts and the ones analyzing only bordering precincts increases our confidence that the former is not driven by the disparate geography or characteristics of LASD- and MPD-served precincts. The results from this analysis combined with those from the previous section provide compelling evidence that support for Measure J was systematically lower among LASD-served precincts. Combined, these findings suggest that service protection was an operative factor in shaping voter support for Measure J.

Exposure to Police Violence and Measure J Support

Model-Based Approach

We now turn to an analysis of the association between exposure to police killings of civilians and voter support for Measure J. Measure J confronted voters with a distinct proposal depending on their LEA jurisdiction and we find robust evidence that support for Measure J was lower on average among LASD-served election precincts. Given this, we estimate the relationship between exposure to police killings and Measure J *%Yes* vote separately for precincts under LASD jurisdiction (N=982) and the jurisdiction of a MPD (N=2,037).

We define *Exposure* to a police killing of a civilian in terms of the geodesic proximity (in miles) of the centroid of a precinct to the exact location of the nearest police killing that occurred within 4 years prior to the 2020 election.[20] Exposure is rescaled to range from -1 to 0, such that -1 implies minimum exposure (i.e., precincts far away from the nearest police killing) and 0 implies maximum exposure (i.e., precincts closest to the nearest police killing).[21] Importantly, given that we analyze the relationship of *Exposure* and Measure J support separately for LASD- and MPD-served precincts, we demonstrate in Figure C12 that the characteristics of police killings by jurisdiction (LASD vs. MPD) are statistically similar across key variables (victim age, gender, race/ethnicity, and armed/unarmed). The sole exception is that police killings occurring in LASD-served precincts were more likely to be the result of gunshots when measuring *Exposure* to include killings 4 or more years prior to the 2020 Election. This difference could be important, as Streeter (2019) finds mobilization against the police is more likely in response to police killings involving death by gunshots.

[20] Proximity is the geodesic distance between a precinct centroid and police killing multiplied by -1. Prior research demonstrates geodesic distance measures are similar to other measures of distance (e.g. driving distance) (Nall, 2015; Reny and Newman, 2018).

[21] For the full dataset, the median exposure to a police killing is -0.03 (1.1 miles away from the nearest police killing), the 25th percentile value is -0.06 (1.8 miles away) and the 75th percentile value is -0.02 (0.7 miles away). Thus, the distribution of *Exposure* is left-skewed. Given this and the possibility of non-linear relationships between *Exposure* and support for Measure J, we estimate alternative models using binary indicators for quartiles of exposure and a logged exposure measure. We find the results hold across these different measures of exposure to police killings (Table C8).

Critically, we demonstrate below that this difference does not drive our results (Figure 4, Panel E), as they remain intact when measuring *Exposure* using only killings occurring within 1 or 3 years prior to the election—which are time intervals where Figure C12 demonstrates no imbalance on death by gunshots or any other characteristics of the killing.

Figure 4, Panels A and B (Table C4), display the association between *Exposure* and support for Measure J in LASD- and MPD-served precincts. Among the former, the association is statistically insignificant and near zero (β = -0.02, se = 0.04); however, among the latter, increasing proximity to the site of a police killing is associated with a statistically significant and substantively large 20 percentage point increase in support for Measure J. The differential relationship of exposure to police killings and Measure J support by LEA jurisdiction displayed in Panels A and B holds when estimating a single regression model including both types of precincts and interacting *Exposure* with the *LASD* variable (Table C13). Panel D reveals that exposure to police killings can make the difference for whether or not MPD-served precincts provide majority support for Measure J. Holding all else constant, precincts furthest from a police killing are estimated to support Measure J by 41%, whereas those closest to a police killing are estimated to support Measure J by 61%. This is notable given that the threshold for passage of Measure J was 50% of the vote. When using alternative versions of our *Exposure* variable altering the time window to include police killings going back either 1, 3, 5 or 10 years before the 2020 election, the results in Panel E (Table C8) demonstrate the estimates for MPD-served precincts remain statistically significant.

We perform a range of additional robustness checks on these results. The results in Figure 4 hold when using beta regression instead of OLS (Table C12) and including city-level fixed effects (Figure C10). Our findings are invariant across the race of victim, with positive and significant associations between *Exposure* and Measure J support for killings involving Black, Latinx or White victims (Figure C14).[22] While most of the police killings in our data involve civilian deaths caused by officer use-of-force (e.g., gunshot, taser, asphyxiation, or

[22]There are no police killings of Asians in the 4 year window prior to the 2020 General Election, so we cannot assess the association between exposure to police killings of Asian civilians and Measure J support.

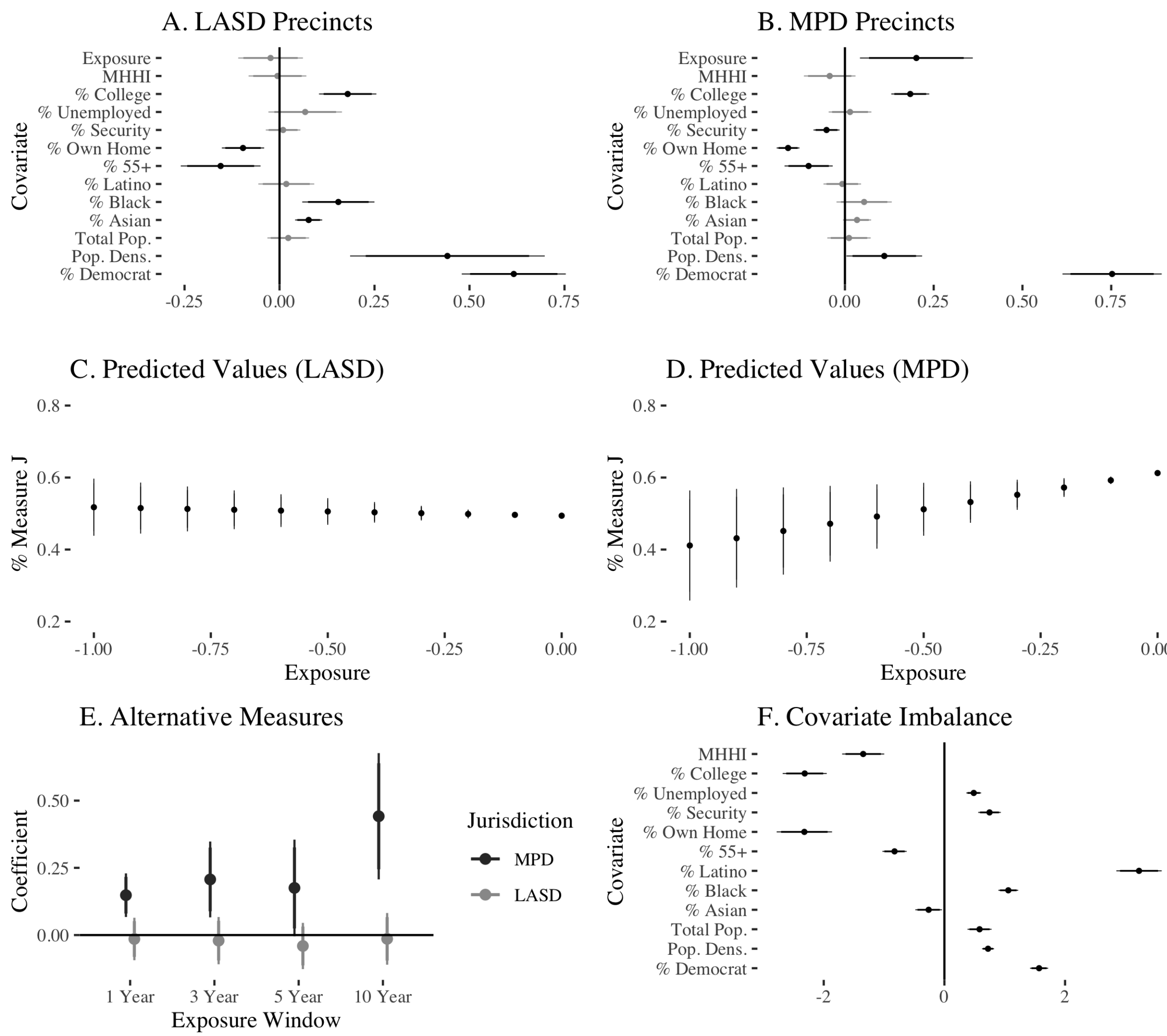

Figure 4: Model-Based Analysis of Exposure to Police Killings and Support for Measure J. Top row displays OLS coefficients from models estimated among LASD-served (A) and MPD-served (B) precincts. Middle row displays predicted Measure J *%Yes* across values of *Exposure* for LASD-served (C) and MPD-served (D) precincts, holding all covariates at their mean. Bottom row displays OLS coefficients for alternative measures of *Exposure* based on police killings occurring 1, 3, 5 and 10 years before the 2020 Election (E) and covariate imbalance between precincts furthest away from and closest to a police killing among MPD-served precincts (F). All covariates except *Exposure* range from 0 to 1. 95% CIs displayed from HC2 robust SEs.

beating, which total up to 81% of police killings in the 4 years prior to the 2020 Election), we demonstrate in Figure C11, Panels A and B, that our results hold when removing from the analysis cases involving deaths by vehicular pursuits, suicides in the presence of officers, and bystander deaths. Given the possibility of data classification errors in the FE database (see Legewie, 2019), we demonstrate that our findings are robust to utilization of an alternative source of information on the police killing of civilians in LAC—namely, *The Homicide Report* compiled by the *Los Angeles Times*,[23] which catalogues all deaths within the county classified by the LAC Medical Examiner-Coroner as a police-involved homicide. Critically, our results hold when re-estimating the models underlying Figure 3, Panels A and B, when using *The Homicide Report* to construct our *Exposure* variable (Figure C11, Panels C-D).

An additional concern underlying our results is that lethal police violence tends to co-occur with homicide in general, as well as higher levels of police presence. Using *The Homicide Report* to calculate the proximity of each precinct to the nearest non-police-related homicide within the 4 years prior to the 2020 Election, we demonstrate in Figure C10 that the influence of *Exposure* to police killings reported in Figure 3, Panel B, holds when controlling for proximity to non-police-related homicide. To account for police presence, we turn again to the police stops data for the cities of Los Angeles and Long Beach (see Section C.5.1). We demonstrate in Figure C10 that the estimated coefficient of *Exposure* to police killings displayed in Figure 3, Panel B, holds when introducing a control for precinct-level police stops per capita. Additionally, we demonstrate that the positive and significant estimate for *Exposure* holds when controlling for both proximity to non-police homicides and the density of police stops (Figure C10, see also Table C9). These findings suggest that the estimated coefficient of *Exposure* to police killings is not due to confounding with exposure to homicide in general or higher levels of police presence. Finally, the results from a placebo test (Figure C13) demonstrate that the observed coefficient for *Exposure* to police killings is always larger than coefficients derived from randomly determined latitude-longitude points throughout LAC, whose average value is zero.

The results in Figure 3 provide firm, yet nuanced, support for the police violence hypothesis. Exposure to lethal police violence appears to have been a strong motivating factor underlying

[23]See `https://www.latimes.com/projects/los-angeles-police-killings-database/`

voter support for the LAC police defunding initiative in 2020; however, this association only emerges under the condition that endorsing police defunding come at *no expense* in prospective police service for one's household or immediate neighborhood. Indeed, when endorsing the initiative involved a potential blow struck against a LEA serving *someone else*, precinct voters exposed to lethal police violence were more likely to wield this blow. Yet, when endorsing the initiative involved a potential blow struck against one's own LEA, exposure to lethal police violence does not appear to have factored into the vote.

Design-Based Approach

Despite our inclusion of a range of covariates and performance of myriad robustness checks, the analysis in the previous section relies on comparisons between potentially very distinct types of precincts, which makes omitted variable bias a lingering concern. We evaluated the association between *Exposure* to police killings and observed control covariates among MPD-served precincts in Figure 4, Panel F. As suspected, we find significant imbalance on all 12 covariates between precincts that are furthest away from and closest to a police killing. The results in Panel F confront us with the fact that our model-based analysis, by comparing precincts close to and far away from police killings, is comparing precincts that are markedly different on an array of demographic, socioeconomic, and political factors.

To complement our model-based analysis, we performed an analysis designed to reduce covariate imbalance and promote comparison between more alike precincts. This approach draws on the analytic strategies employed in two leading studies. The first is by Ang (2021), who leverages hyperlocal exposure to police killings of civilians in LAC to analyze the impact of lethal police violence on the educational performance and emotional well-being of school children. This approach defined the "treatment" as living very close (e.g., < 0.5 miles) to the site of a police killing of a civilian. The second is by White (2019a), who investigates the impact of proximal carceral contact on voter turnout by analyzing only "treated" units (i.e., voters with proximal carceral contact) and draws the main analytic comparison between units treated shortly before an analyzed election and those treated shortly after.

Drawing on these studies, we pursue a design-based approach that restricts the analysis to only include precincts in close proximity to the site of a police killing of a civilian. Using this subset of only "treated" precincts, we focus our analytic comparison on the difference in Measure J support between precincts where the nearby police killing occurred shortly before versus shortly after the November 2020 Election. The idea underlying this design is that analyzing precincts mutually exposed to lethal police violence will render more alike units of analysis, with the principle point of comparison being that one set of precincts experienced a police killing prior to the election, thus heightening the salience of police violence for these voters before casting their ballots. To proceed with this analysis, we needed to determine (a) spatial thresholds for defining living very close to a police killing (i.e., being a "treated" precinct), and (b) temporal bandwidths surrounding the election. One concern in determining these quantities is researcher degrees of freedom and the potential sensitivity of results to specific cutoffs. Our solution was to conduct analyses using multiple spatial thresholds and temporal bandwidths to determine the presence of a consistent pattern of findings.

With respect to spatial thresholds, we include precincts whose centroids were less than 0.5, 0.75, or 1.0 mile away from the site of a police killing of a civilian. The lowest threshold of 0.5 miles is based on Ang (2021), who uses 0.0 to 0.5 of a mile range from the location of a police killing as the spatial interval for treatment assignment. Other scholarship analyzing the impact of exposure to aggressive policing use impact zones that range from 1 to 16km^2 (Legewie and Fagan, 2019), census block groups ranging from 0.01 to 18km^2 (Lerman and Weaver, 2014a), and voter tabulation districts as large as 10km^2 (Laniyonu, 2019). Each of these studies presume that their units of analysis are exposed to the police behavior measured at these varying levels of geographic aggregation. To mitigate concerns about the reliance of our results on a single threshold for defining "exposure", we also include in our analysis thresholds of <0.75 and <1.0 mile. With respect to temporal bandwidths, we include police killings of civilians occurring within 3, 4 or 5 month windows before and after the November

2020 Election. White (2019a) documents balance on a range of covariates when comparing voters experiencing the arrest of a household member up to ± 40 weeks surrounding the 2012 Election, and research on exposure to aggressive policing and police killings document treatment effects lasting up to 2 years (Legewie and Fagan, 2019; Ang, 2021). Our use of ± 3, 4 or 5 month bandwidths is consistent with the operationalization of exposure to police killings in recent epidemiological research (Bor et al., 2018b), mitigates concern about the reliance of our results on a single definition of "closeness" to the election, and are empirically grounded in tests for covariate balance presented below.

These differing spatial thresholds and temporal bandwidths amount to 9 distinct distance-time pairings eligible for analysis.[24] The independent variable in this analysis for each of our 9 distance-time pairs is a dichotomous variable, labeled *Exposure*, indicating whether a precinct's exposure to lethal police violence occurred before (coded '1') versus after (coded '0') the election. A central assumption of this analytic approach is that precincts exposed to a police killing shortly before the election will be similar on baseline covariates to precincts exposed shortly after the election. Figure 5 displays the balance on 14 baseline demographic, socioeconomic, and political covariates[25] between precincts close to police killings occurring before versus after the election for each of the 9 distance-time pairs used to construct the sample under analysis. Relative to the model-based approach, this design-based approach yields a drastic reduction in covariate imbalance. The results in Figure 4, Panel F, reveal that precincts close to police killings are significantly less populated, White, wealthy, educated, employed, home-owning, elderly, and Republican than precincts far away from police killings. Figure 5 indicates that nearly all of these significant imbalances are removed when confining the analysis to only "treated" precincts close to police killings that differ in the timing of

[24] In the <3, <4, and <5 month samples, there are 10, 12, and 19 police killings prior to the 2020 election respectively. Likewise, there are 11, 16, and 23 police killings after the 2020 election respectively. Prior to the 2020 election, the median date for a police killing in the <3, <4, and <5 month samples is 2020-10-06, 2020-09-10, and 2020-08-14. After the 2020 election, the median date is 2020-12-19, 2021-01-10, and 2021-02-03.

[25] This includes the 12 covariates included in previous analyses and the addition of tests for imbalance on precinct proximity to non-police homicide and exposure to police killings from t-5 months through 10 years prior to the 2020 Election

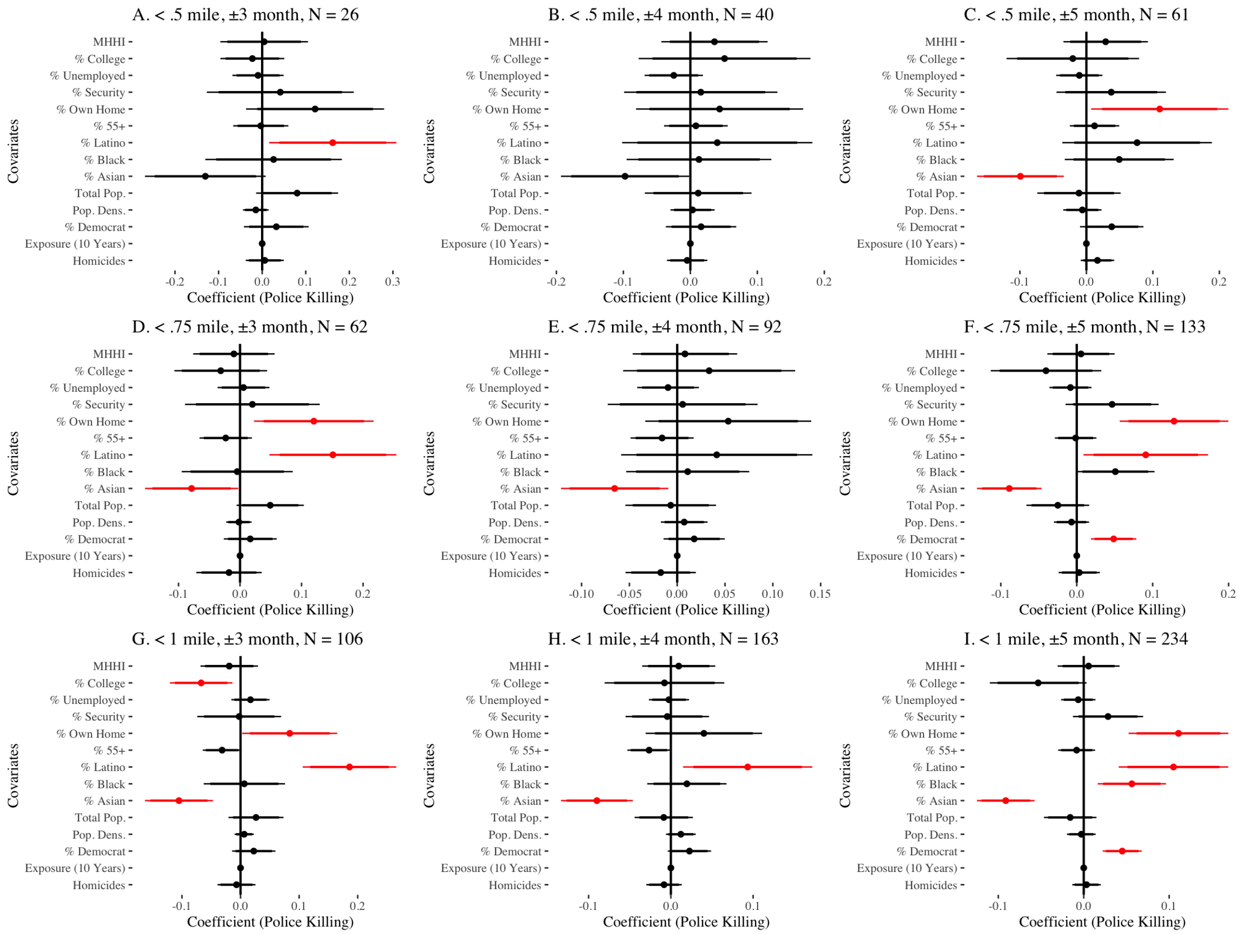

Figure 5: Balance Plots Across Distance-Time Pairings. All panels display estimated coefficients from bivariate OLS models regressing each listed covariate on Y-axis on *Exposure* to police killings before (versus after) the 2020 Election. Sample size for each distance-time pair displayed on each panel title. All covariates scaled between 0-1. Color denotes statistical significance (red = significant, black = insignificant).

the killing around the election. As a general summary of Figure 5, we observe the strongest covariate balance when focusing on precincts exposed to police killings ±4 months of the election and balance tends to worsen when using wider distance-time cutoffs.

One point of caution about the present analytic approach is the trade-off inherent in the data between reduced covariate imbalance and sample size. While Ang (2021) and White (2019a) analyze large samples of school children and voters, our analysis is capped at 3,019 election precincts; and, subsetting the data by spatial proximity to police killings and temporal closeness to the election greatly reduces the sample size eligible for analysis. As can be seen by sample sizes reported in Figure 5, narrowing down the distance-time cutoffs, while tending to improve balance, renders smaller sample sizes. Given this, we view the value of the analytic approach employed in this section largely in terms of a demonstration of the robustness of the model-based results when sacrificing statistical power for a drastic reduction in covariate imbalance. We have already found that spatial proximity to police killings is positively associated with support for Measure J. If we also find that support for Measure J was higher among the small subset of precincts close to a police killing occurring months before the election compared to the small subset of precincts close to a killing occurring in the months after, we would have added confidence that lethal police violence factored into voter support for Measure J. In short, while neither our model-based nor the present design-driven approach are without their limitations, uncovering corroborating findings using both approaches offers stronger evidence in support of the police violence hypothesis.

The results from our design-driven analysis are presented in Figure 6 (Table D20). For each distance-time pair, we present the coefficient estimate for the *Exposure* variable from a bivariate regression model and, if applicable, a model controlling for any covariates for which results in Figure 5 indicate statistically significant imbalance.[26] Across the board, exposure to a police killing before relative to after the election is associated with greater support for Measure J. Out of the 9 coefficient estimates from bivariate models, 7 are positive and statistically significant. Moreover, for the 8 out of 9 distance-time pairings containing some covariate imbalance, the estimated coefficient for *Exposure* is either marginally or conventionally statistically significant in 5 out of 8 tests. In total, out of 17 tests, we find at least a marginally significant positive coefficient for *Exposure* in 12 instances (i.e., roughly 71% of the time). When the coefficient is at least marginally statistically significant, the effect of exposure to a police killing just before the election is between 2-6 percentage points.

[26]For example, for the distance-time pair of <0.5 miles and ± 4 months, there is no imbalance on baseline covariates (Figure 5, Panel B), therefore, there is no corresponding coefficient estimate displayed that adjusts for imbalanced covariates. For the distance-time pair of <0.75 miles and ± 4 months, there is imbalance on *%Asian* (Figure 5, Panel E); therefore, two coefficients for *Exposure* are displayed: one from a bivariate model and one from a model controlling for *%Asian*

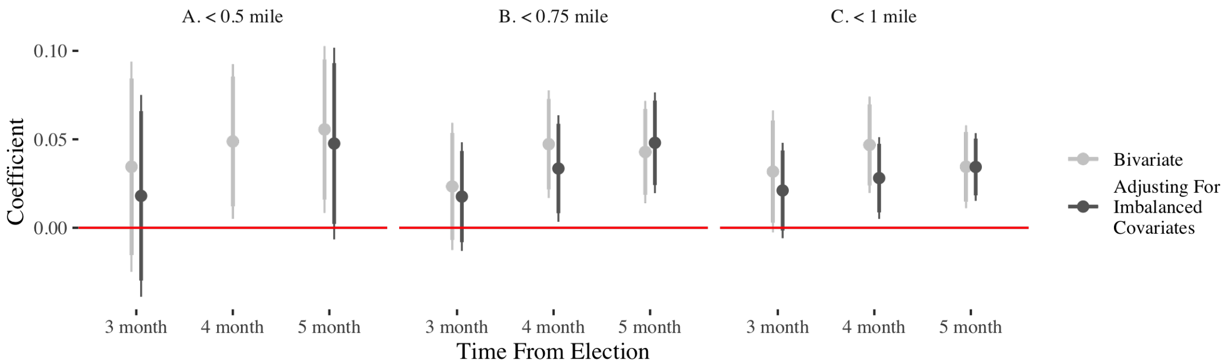

Figure 6: Design-Based Analysis of Exposure to Police Killings and Support for Measure J (MPD-Served Precincts). Panels display different spatial thresholds for defining *Exposure* and columns display different temporal bandwidths around the 2020 Election. Coefficient color denotes bivariate models (light grey) and models controlling for persisting imbalanced covariates (black). 95% CIs displayed derived form HC2 robust SEs.

This effect is substantively large, equivalent to 15-46% of the standard deviation in *%Yes* vote for Measure J for MPD-served precincts.

We conducted several checks on these results. First, it is possible our results are driven by differences in the characteristics of the police killings occurring before versus after the election that may be linked to the salience of the killings (e.g., race, gender or age of victim; victim armed/unarmed; amount of media coverage). Figure D15 reveals that the killings included at 3, 4 or 5 month bandwidths do not significantly differ across key characteristics by the timing of the killing around the election. These insignificant findings help alleviate the concern that the results in Figure 6 are driven by pre-election police killings possessing distinctive characteristics rendering them more salient. Second, we re-ran the analysis substituting as the dependent variable precinct voter support for five criminal justice ballot initiatives held in earlier elections (i.e., those analyzed in Figure 2, Panels B-C). The logic here is that a "treatment" (i.e., police killing) occurring within 3 to 5 months before versus after November 2020 should not affect the behavior of precinct voters on initiatives held years before the treatment events in question. The results in Figures D16-D20 reveal mostly null effects, suggesting that the findings presented in Figure 5 are not due to a coincidence where the precincts close to police killings occurring within 3-5 months before the 2020 Election happen to have a preexisting tendency of liberalism on criminal justice policy relative to precincts close to police killings occurring 3-5 months after the election.

Third, we demonstrate in Figure D23 that the pattern of results observed in Figure 5 do not emerge when using exposure to non-police homicides as the "treatment" variable. For this analysis, we identified all precincts within 0.5, 0.75 or 1 mile of a non-police homicide occurring within 3, 4 or 5 month bandwidths around the election and generated an alternative *Exposure* variable coded '1' if the nearby non-police homicide occurred before the election and '0' if after. In most instances, precincts close to non-police homicides occurring before the election did not significantly differ, or were slightly less supportive, of Measure J than those close to non-police homicides occurring after the election. These diverging findings are critical, as they illustrate that the results in Figure 5 are unique to exposure to police killings and not to homicide in general. Finally, commensurate with our model-based results, we find exposure to police killings before (versus after) the 2020 Election did not appear to motivate support for Measure J among LASD-served precincts. The results in Figure D22 demonstrate that 5 out of 9 estimates adjusting for persisting imbalanced covariates are statistically null and the statistically significant estimates are in the opposite direction.[27]

Conclusion

The Black Lives Matter movement has grown over the past 8 years in response to recurrent police killings of unarmed civilians. Several localities have responded to the issue of excessive violence in policing by considering or implementing policies intended to constrain the police.[28] Arguably at the frontier of the American progressive justice reform movement are calls to "defund the police." The DTP movement is distinctly controversial in the terrain of justice

[27]Moreover, relative to MPD-served precincts, there is a higher degree of persisting covariate imbalance across the distance-time pairs for LASD-served precincts exposed to police killings shortly before versus after the election (see Figure D21), with no distance-time pair yielding less than 3 imbalanced covariates.

[28]See `https://ballotpedia.org/Changes_to_policing_policy_in_the_states_and_100_largest_cities_2020` for a comprehensive record of policies considered or implemented by the 100 largest cities in the United States in response to calls for police reform after the 2020 BLM protests.

reform politics in the United States given that DTP policies putatively involve a trade-off between carceral state retrenchment and public safety. Using the case of Measure J in LAC, we assess if election precincts exposed to lethal police violence were more likely to support the diversion of funding for the LASD to social spending and alternative public safety programs. Given not all precincts in LAC are served by the county sheriff's office, some LAC precincts were voting to reduce funding for their own LEA while others were not. We find that precincts under the jurisdiction of the LASD were less supportive of the initiative; moreover, we find that precincts exposed to police killings were more likely to support the defunding measure, but only under the condition that doing so did not involve reduced funding for their own LEA. In this way, our findings reflect broader public discourse surrounding DTP, which typically pit curtailing police violence against maintaining public safety.

The findings in this article add to the mounting literature on the mobilizing effect of exposure to the carceral state. Prior research demonstrates a sense of injustice motivates political participation in response to carceral contact (Drakulich et al., 2017; Walker, 2020). Other research shows precincts exposed to excessive stop-and-frisks vote for reformist mayoral candidates that may seek to constrain the police (Laniyonu, 2019). Extending this work, our findings suggest that when voters have an opportunity to presumably constrain the police by reducing and diverting funding, an important motivator of voter support for doing so is exposure to lethal police violence. Our findings may serve as a source of optimism for reformers who seek to implement alternative solutions to policing that could provide public safety. However, a critical contribution inherent to our findings is that political mobilization in response to police killings may be stunted by service protection considerations and perceptible trade-offs in public safety. One implication of this is that future efforts to DTP may have to grapple with the traction among voters of arguments against DTP evoking concerns about crime and the maintenance of public safety. Interestingly, organizers in LAC were successful in helping pass Measure J in part due to their avoidance of the moniker "defund the police" and their emphasis on what the measure would fund versus what it would defund. In our view, assessing frames that may motivate support (or lack thereof) for DTP is an important area of future research (Peyton et al., 2020).

Having noted its contributions, it is important to discuss the limitations of our analyses. First, since voter file data does not contain information on individual vote choices, the best available option was for us to analyze precinct-level data (the smallest unit of geographic aggregation) on vote choice for Measure J. Therefore, we caution readers in making inferences concerning individual voters on the basis of our empirical findings. This said, our analysis includes many very small precincts in dense urban areas throughout LAC that include relatively homogeneous collections of voters. One direction for future research would be to test if exposure to police killings motivates support for DTP using individual survey data. Such research, while possessing the benefit of individual-level observation, would carry the limitation of analyzing the reported, versus revealed, preferences of voters. Second, although our findings are robust to model- and design-based approaches, neither approach is perfect: the former offers larger sample size and statistical power but comes with concerns about comparing substantially dissimilar precincts while the latter offers drastic reductions in covariate imbalance yet comes with concerns about reduced sample size and statistical power. In our view, the strength of this article lies in uncovering corroborating results across distinct analytic approaches. Finally, it is important to note that our findings are based on a single case, creating an opportunity for research to assess whether or not the relationships observed in LAC hold for DTP initiatives voted upon in other contexts.

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Appendices

Contents

A Measure J Voter Information Materials

A.1 Sample Ballot

Sample Ballot

General Election
November 3, 2020

DISTRICT

ANTELOPE VALLEY HEALTH CARE DISTRICT Member, Board of Directors
Vote For No More Than **THREE**

- KRISTINA HONG — Emergency Nurse
- MATEO B. OLIVAREZ — Incumbent
- ABDALLAH S. FARRUKH — Incumbent
- KEVIN L. VON TUNGELN — Business Owner
- MICHAEL P. RIVES — Retired Hospital Worker
- Write-In Candidate
- Write-In Candidate
- Write-In Candidate

COUNTY

DISTRICT ATTORNEY
Vote For **ONE**

- JACKIE LACEY — Los Angeles County District Attorney
- GEORGE GASCÓN — Justice Reform Advocate
- Write-In Candidate

JUDGE OF THE SUPERIOR COURT Office No. 72
Vote For **ONE**

- STEVE MORGAN — Deputy District Attorney, County of Los Angeles
- MYANNA DELLINGER — Law Professor/Attorney
- Write-In Candidate

JUDGE OF THE SUPERIOR COURT Office No. 80
Vote For **ONE**

- DAVID A. BERGER — Deputy District Attorney, County of Los Angeles
- KLINT JAMES MCKAY — Administrative Law Judge, California Department of Social Services
- Write-In Candidate

JUDGE OF THE SUPERIOR COURT Office No. 162
Vote For **ONE**

- DAVID D. DIAMOND — Attorney/Law Professor
- SCOTT ANDREW YANG — Deputy District Attorney, County of Los Angeles
- Write-In Candidate

J COUNTY MEASURE J
Vote **YES** or **NO**

COMMUNITY INVESTMENT AND ALTERNATIVES TO INCARCERATION MINIMUM COUNTY BUDGET ALLOCATION. Shall the measure, annually allocating in the County's budget no less than ten percent (10%) of the County's locally generated unrestricted revenues in the general fund to address the disproportionate impact of racial injustice through community investment and alternatives to incarceration and prohibiting using those funds for carceral systems and law enforcement agencies as detailed in the ordinance adopting the proposed charter amendment, be adopted?

- YES on Measure J
- NO on Measure J

STATE

14 STATE MEASURE 14
Vote **YES** or **NO**

AUTHORIZES BONDS CONTINUING STEM CELL RESEARCH. INITIATIVE STATUTE. Authorizes $5.5 billion state bonds for: stem cell and other medical research, including training; research facility construction; administrative costs. Dedicates $1.5 billion to brain-related diseases. Appropriates General Fund moneys for repayment. Expands related programs. Fiscal Impact: Increased state costs to repay bonds estimated at about $260 million per year over the next roughly 30 years.

- YES on Measure 14
- NO on Measure 14

Continue voting on next page

EN-NP-0001-1-2 LA 001-012

Figure A1: Sample Ballot Information On Measure J.

A.2 Measure J Information

Candidate Statements & Measures

FULL TEXT OF BALLOT MEASURE J

ORDINANCE NO. 2020-0040

An ordinance calling a special election to be held on November 3, 2020, throughout the County of Los Angeles for the purpose of voting upon an amendment to the Los Angeles County Charter and directing the consolidation of the election with the statewide general election to be held on the same day.

The Board of Supervisors of the County of Los Angeles ordains as follows:

SECTION 1. Call of Election and Purpose. A special election is hereby called, proclaimed and ordered to be held on November 3, 2020, for the purpose of voting upon a proposed amendment to the Charter of the County of Los Angeles.

SECTION 2. Resolution Establishing Form of Proposition. The exact form of the Proposition as it is to appear on the ballot and the complete text of the proposed amendment is as follows:

PROPOSED COUNTY CHARTER AMENDMENT. COMMUNITY INVESTMENT AND ALTERNATIVES TO INCARCERATION MINIMUM COUNTY BUDGET ALLOCATION. Shall the measure, annually allocating in the County's budget no less than ten percent (10%) of the County's locally generated unrestricted revenues in the general fund to address the disproportionate impact of racial injustice through community investment and alternatives to incarceration and prohibiting using those funds for carceral systems and law enforcement agencies as detailed in the ordinance adopting the proposed charter amendment, be adopted?	YES NO

PROPOSITION J

This Proposition shall become effective only if it is submitted to the voters at the election held on November 3, 2020 and is approved. The Charter amendment shall become operative on July 1, 2021.

First: Section 11 of Article III of the Charter of the County of Los Angeles is amended to read:

Section 11. It shall be the duty of the Board of Supervisors:

(1) To appoint all County officers other than elective officers, and all officers, assistants, deputies, clerks, attaches [14] and employees whose appointment is not provided for by this Charter. [15]

...

(8) To allocate, in compliance with all laws and regulations, the County's locally generated unrestricted revenues in the general fund as follows:

A. Set aside a baseline minimum threshold of at least ten percent (10%) of the County's locally generated unrestricted revenues in the general fund (Net County Cost), as determined annually in the budget process or as otherwise set forth in the County Code or regulations, to be allocated on an annual basis, after input from, among others, the public and County departments at a public hearing, for the following primary purposes:

i. Direct Community Investment.

1. Community-based youth development programs.

2. Job training and jobs to low-income residents focusing on jobs that support the implementation of the "Alternatives to Incarceration" workgroup recommendations as presented to the County Board of Supervisors on March 10, 2020, especially construction jobs for the expansion of affordable and supportive housing, restorative care villages, and a decentralized system of care.

3. Access to capital for small minority-owned businesses, with a focus on Black-owned businesses.

4. Rent assistance, housing vouchers and accompanying supportive services to those at-risk of losing their housing, or without stable housing.

5. Capital funding for transitional housing, affordable housing, supportive housing, and restorative care villages with priority for shovel-ready projects.

ii. Alternatives to Incarceration.

1. Community-based restorative justice programs.

2. Pre-trial non-custody services and treatment.

3. Community-based health services, health promotion, counseling, wellness and prevention programs, and mental health and substance use disorder services.

4. Non-custodial diversion and reentry programs, including housing and services.

4193-EN-00012

LA 001-034

Figure A2: Information on Measure J Mandates (Part 1)

Candidate Statements & Measures

B. The set aside shall not be used for any carceral system or law enforcement agencies, including the Los Angeles County Sheriff's Department, Los Angeles County District Attorney's Office, Los Angeles County Superior Courts, or Los Angeles County Probation Department, including any redistribution of funds through those entities. This restriction does not extend to State law requiring the County to fund court facilities and expenditures, including, but not limited to, the Trial Court Facilities Act of 2002 (2002 Senate Bill No. 1732) and Lockyer-Isenberg Trial Court Funding Act of 1997 (1997 Assembly Bill No. 233), other mandatory fines and fees, or any other County commitments to the extent required by law.

C. The unrestricted revenues that are set aside shall phase in over a three-year period, beginning July 1, 2021, and incrementally grow to the full set-aside by June 30, 2024, pursuant to the procedures codified in the County Budget Act in the Government Code.

D. The set aside cannot supplant monies otherwise allocated for the same categories listed in Subsection (8)(A), as defined and set forth in the County Code or regulations.

E. The Board of Supervisors shall establish an inclusive and transparent process on the allocation of funds set aside by this Subsection (8).

F. Notwithstanding this Subsection (8), the Board of Supervisors may, by a four-fifths vote, reduce the set-aside in the event of a fiscal emergency, as declared by the Board of Supervisors, that threatens the County's ability to fund mandated programs.

Second: In the event that the amendment to the Charter of Los Angeles County contained in this Proposition is rendered inoperative because of the actions of any court, legislative or other body, or for any other reason, the provisions of the County Charter in effect on November 3, 2020, shall remain in full force and effect.

Third: If any section, subsection, subdivision, paragraph, sentence, clause, phrase, or word of this Proposition is for any reason held to be invalid or unenforceable, such invalidity or unenforceability shall not affect the validity or enforceability of the remaining sections, subsections, subdivisions, paragraphs, sentences, clauses, phrases, or words of this amendment to Section 11 of Article III of the Charter. The voters of the County of Los Angeles declare that they would have independently adopted each section, subsection, subdivision, paragraph, sentence, clause, phrase, or word of this Proposition irrespective of the fact that any one or more other sections, subsections, subdivisions, paragraphs, sentences, clauses, phrases, or words of this amendment to Section 11 of Article III is declared invalid or unenforceable.

SECTION 3. Consolidation. The special election shall be consolidated with the statewide general election to be held on Tuesday, November 3, 2020. The Proposition shall be placed upon the same ballot as that provided for the general election. The precincts, polling places, or vote centers, and precinct board members shall be the same as provided for the statewide general election.

SECTION 4. Proclamation. Pursuant to section 12001 of the Elections Code, the Board of Supervisors of the County of Los Angeles hereby PROCLAIMS that a special countywide election shall be held on Tuesday, November 3, 2020, to vote upon the Charter Amendment described in Section 2 of this Ordinance.

SECTION 5. Effective Date. Pursuant to Section 9141 of the Elections Code and Section 25123 of the Government Code, this Ordinance shall take effect upon the adoption thereof.

SECTION 6. Authority. This Ordinance is adopted pursuant to sections 23720, 23730, and 23731 of the Government Code, and sections 9141,10402, 10403, and 12001 of the Elections Code.

SECTION 7. Publication. This Ordinance shall be published once before the expiration of 15 days after its passage in a daily newspaper of general circulation, printed, published and circulated in the County of Los Angeles pursuant to Government Code section 25124.

The Executive Officer-Clerk of the Board of Supervisors is ordered to file a copy of this Ordinance with the Registrar-Recorder at least 88 days prior to the day of the election.

4193-EN-00013 LA 001-035

Figure A3: Information on Measure J Mandates (Part 2)

A.3 Measure J Impartial Analysis

Candidate Statements & Measures

IMPARTIAL ANALYSIS OF MEASURE J

By Mary C. Wickham, County Counsel

Measure J is a proposed charter amendment placed on the ballot by the Los Angeles County Board of Supervisors ("Board"). If approved by the voters, the measure would implement an ordinance amending Section 11 of Article III of the Charter of the County of Los Angeles ("County").

The measure would set aside at least ten percent (10%) of the County's locally generated unrestricted revenues in the general fund, as determined annually in the budget process or as set forth in the County's Code or regulations, to be annually allocated towards the following primary purposes:

- Direct Community Investment, including: community-based youth development programs; job training and jobs to low-income residents; access to capital for small minority-owned businesses; rent assistance, housing vouchers and supportive services to those at-risk of losing their housing or without stable housing; capital funding for transitional housing, affordable housing, supportive housing and restorative care villages; and,

- Alternatives to Incarceration, including: community-based restorative justice programs; pre-trial non-custody services and treatment; community-based health services, such as counseling, wellness and prevention programs, mental health and substance use disorder services; and non-custodial diversion and reentry programs.

The set-aside revenues cannot replace monies otherwise allocated for the foregoing categories as set forth in the County's Code or regulations.

The measure would prohibit the set-aside revenues from being used for any carceral system or law enforcement agencies, including the County's Sheriff's Department, District Attorney, Probation Department, or the Los Angeles County Superior Courts, and would prevent redistribution of funds through those entities. This prohibition would not extend to court facilities and expenditures required pursuant to State law, including the Trial Court Facilities Act of 2002, the Lockyer-Isenberg Trial Court Funding Act of 1997, other mandatory fines and fees, or any other County commitments required by law.

The measure would enable set-aside revenues to phase in over a three-year period beginning on July 1, 2021, to the full set-aside amount by June 30, 2024. The measure requires the Board to establish an inclusive and transparent process for the allocation of the set-aside funds.

While the measure, if approved by the voters, may be repealed only by a subsequent vote of the electorate on an amendment to the Los Angeles County Charter, the Board may, by a four-fifths vote, reduce the set-aside in the event of a declared fiscal emergency that threatens the County's ability to fund mandated programs.

The measure requires a majority vote for passage.

4193-EN-00014

LA 001-036

Figure A4: Impartial Analysis of Measure J

A.4 Measure J Argument in Favor

Candidate Statements & Measures

ARGUMENT IN FAVOR OF MEASURE J

Vote YES on Measure J to address the disproportionate impact of racial injustice by prioritizing health, housing, youth development and jobs in low-income and underserved communities—with a particular focus on Black, Brown, and low-income communities.

Vote YES on Measure J to make sure that a minimum of 10% of EXISTING local county revenue is guaranteed to be invested in community safety, housing stability, and care.

Vote YES on Measure J because it is clear that now is the moment to re-imagine L.A. County and make sure our county government budget reflects our shared values and priorities.

Vote YES on Measure J to:

--Increase community based counseling and mental health services
--Prioritize restorative justice programs
--Expand job training and placement support
--Create housing that is affordable to working people
--Support small businesses
-Scale up mentoring and youth development programs

Vote YES to shift resources from the criminal justice system to programs proven to address the root causes of crime. Incarceration and punishment are ineffective at treating poverty, mental illness, and a lack of housing.

Vote YES on Measure J because it is fiscally responsible and holds our elected leaders accountable. This is NOT a new tax--instead it will gradually and responsibly phase in the 10% budget set aside of existing local revenues over a four-year period. The funding set aside could be paused by the Board of Supervisors in a fiscal emergency. The measure promotes transparency by requiring an annual budgeting process that is flexible, but with a clear framework of eligible and non-eligible uses.

In these unprecedented times, we need real, meaningful change. Vote YES on Measure J to prioritize health, housing, and economic investment in communities across L.A. County.

ELISE BUIK
President & CEO, United Way of Greater L.A.

PATRISSE CULLORS
Chair, Reform L.A. Jails

HECTOR VILLAGRA
Executive Director, ACLU of Southern California

DAN LANGFORD
Executive Secretary-Treasurer and CEO,
SW Regional Council of Carpenters

ISAAC BRYAN
Director of Public Policy, UCLA Ralph J. Bunche
Center for African American Studies

4193-EN-00015

LA 001-037

Figure A5: Argument in Favor of Measure J

A.5 Measure J Argument in Favor Rebuttal

Candidate Statements & Measures

REBUTTAL TO ARGUMENT IN FAVOR OF MEASURE J

VOTE NO on MEASURE J – the $500,000,000.00 essential services cut.

Measure J fails to solve racial injustice.

— Measure J asks voters to "Re-imagine LA" where racial injustice will somehow be fixed by PERMANENTLY cutting nearly $500,000,000.00 from essential services provided by the county's emergency response workers, nurses, 911 operators, social workers, and more.

— Measure J PERMANENTLY diverts nearly $500,000,000.00 to unspecified programs that sound politically appealing today, but cannot be effectively implemented by County Supervisors.

Measure J hurts the people they say they're trying to help.

— Many of the people and communities who need additional investments to succeed in today's difficult economy would lose nearly half a billion dollars in resources under Measure J.

— Workers who provide essential county services more often come from and serve communities of color. Measure J PERMANENTLY shifts nearly $500,000,000.00 away from those essential services and jobs into growing the government bureaucracy.

Measure J PERMANENTLY diverts nearly $500,000,000.00 into the hands of county politicians who keep failing us.

— Voters gave County Supervisors millions of dollars to fix homelessness. The crisis has only gotten worse.

— Voters entrusted County Supervisors to help us get through the COVID-19 health crisis. LA County has the most infections and deaths in California while more people face unemployment as businesses shutter.

County Supervisors keep failing to solve the crises threatening our safety and well-being right now.

Why would we PERMANENTLY give County Supervisors $500,000,000.00 to keep failing us on a whole new set of unspecified programs?

VOTE NO on MEASURE J.

More information at NoMeasureJ.com

DON KNABE
Los Angeles County Supervisor, Retired

LAMBERT ADOUKI
Long Beach Community Organizer

DAVID SIFUENTES
Retired Firefighter

RICHARD CLOSE
Sherman Oaks Homeowners Association President

KATHLEEN CADY
Children's Advocacy Center Co-Founder

4193-EN-00016

LA 001-038

Figure A6: Rebuttal Against Argument in Favor of Measure J

A.6 Measure J Argument in Disfavor

Candidate Statements & Measures

ARGUMENT AGAINST MEASURE J

Measure J has good intentions, but the consequences will be painful.

Vote No on Measure J.

No on Measure J – the county is struggling just to provide existing services

- Measure J permanently diverts nearly $500,000,000.00 away from essential workers and critical public services county residents already rely on to a broad wish list of unspecified programs county government isn't equipped to manage.

- The county is still struggling to help get us through the COVID-19 crisis and decrease homelessness.

- Permanently diverting hundreds of millions of dollars from essential services into a whole new set of unspecified programs during a health and economic crisis will hurt the people it's designed to help.

No on Measure J – puts the safety of our neighborhoods at risk

- Measure J permanently takes $500,000,000.00 in funding away from where it is needed the most—emergency response workers, nurses, 911 operators, public safety officers, social workers, and other essential workers.

No on Measure J – big political promises and no explanation of consequences

- The Los Angeles Times called it a "bad idea" and a "poor substitute for careful study, deliberation, and decision making."

- Measure J is cloaked in progressive words and big political promises, but no plan to implement and no specific fiscal accountability to make sure the money is spent effectively.

- Four county politicians rushed Measure J to the ballot without assessing the consequences of how permanently diverting nearly half a billion dollars away from essential county services will harm our neighborhoods.

We all want more people in Los Angeles to succeed, but all Measure J actually does is permanently divert nearly $500,000,000.00 away from essential county services into a whole new wish list of programs the county can't effectively manage.

Vote No on Measure J.

More information: ProtectEssentialWorkers.com

KATHRYN BARGER
Chair, Los Angeles County Board of Supervisors

DAVID SIFUENTES
Retired Firefighter

LAMBERT ADOUKI
Long Beach Community Organizer

MARIA BOWSA
Retired Registered Nurse

4193-EN-00017

LA 001-039

Figure A7: Argument in Disfavor of Measure J

A.7 Measure J Argument in Disfavor Rebuttal

Candidate Statements & Measures

REBUTTAL TO ARGUMENT AGAINST MEASURE J

Vote Yes on Measure J

For far too long our underserved and marginalized communities across L.A. County have been left out and left behind, with fatal public health consequences. Measure J will change this.

The lack of investment has driven higher levels of poverty and shorter life expectancy for Black, Brown and low-income people. The pandemic has made this inequity even more clear.

While voting YES on Measure J is about creating a more just and equitable future that reflects our shared values, the opponents of Measure J prefer to use fear tactics to maintain the broken status quo.

Over 100 organizations with a track record of fighting for justice, community investment, health and wellness say Yes on Measure J.

National Union of Healthcare Workers, Black Lives Matter L.A., Community Coalition, Frontline Wellness Network, UNITE HERE! Local 11, and many more have all called for bold and permanent action to improve public safety and prioritize our communities. Measure J does exactly that.

--YES on Measure J – Increases public safety by funding programs that proactively address and treat the root causes of crime.

--YES on Measure J – Increases public safety by funding mental health treatment and counseling.

--YES on Measure J – Ensures that at least 10% of EXISTING County funds are fairly dispersed through a transparent, inclusive process for impacted communities--rather than being allocated through backroom deals to campaign contributors.

Re-Imagine L.A. County, vote YES on Measure J.

www.MeasureJforLA.com

BELTRAN CHOW, LCSW
Enriched Residential Services Program Coordinator

DAHLIA FERLITO, MPH
Health Educator

LIZ SUTTON, LCSW
Enriched Residential Services Program Manager

ANDREA PASQUINI
Registered Nurse

4193-EN-00018

LA 001-040

Figure A8: Rebuttal Against Argument in Disfavor of Measure J

B Internet Search Interest and Social Media Mentions of "Defund the Police" in LA Metro Area Before and After 2020 Election

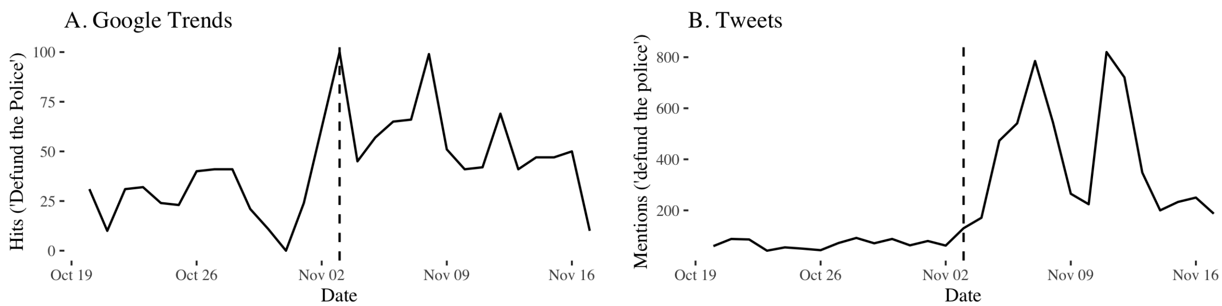

Figure B9: Residents in LA Metro Area sought information about and commented on "Defund the police" in the lead up to and following the 2020 Election. Panel A displays the daily (x-axis) intensity of Google searches (y-axis) in the Los Angeles metropolitan region for "defund the police" in the two weeks before and after the Measure J vote. Panel B displays the daily (x-axis) number of tweets (y-axis) in the Los Angeles metropolitan region that included "defund the police" in the two weeks before and after the Measure J vote. The dashed vertical line denotes the moment Measure J was voted on.

C Model Based Approach

C.1 Regression Tables

C.1.1 LASD Model

Table C1: Association between LASD jurisdiction and support for Measure J

	% Measure J	
LASD	-0.11^{***}	-0.02^{***}
	(0.01)	(0.00)
MHHI		-0.03
		(0.03)
% College		0.18^{***}
		(0.02)
% Unemployed		0.02
		(0.03)
% Security		-0.02
		(0.02)
% Own Home		-0.14^{***}
		(0.01)
% 55+		-0.15^{***}
		(0.03)
% Latino		-0.02
		(0.02)
% Black		0.07^{**}
		(0.02)
% Asian		0.05^{***}
		(0.01)
Total Pop.		0.02
		(0.02)
Pop. Dens.		0.15^{**}
		(0.05)
% Democrat		0.74^{***}
		(0.04)
R^2	0.12	0.70
N	3019	3019

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All covariates rescaled between 0-1. HC2 robust standard errors in parentheses.

C.1.2 LASD Falsification Tests

Table C2: Influence of LASD on Support for Other CJ Propositions

	Meas. J (2020) (1)	**Prop. 57 (2016)** (2)	**Prop. 47 (2014)** (3)	**Prop. 36 (2012)** (4)	**Prop. 5 (2008)** (5)	**Prop. 66 (2004)** (6)
LASD	-0.025^{***}	-0.012^{***}	-0.012^{***}	-0.007^{***}	-0.005^{*}	-0.008^{***}
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
MHHI (2000)	-0.14^{***}	-0.00	-0.06^{**}	-0.01	-0.05^{*}	-0.01
	(0.04)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
% College (2000)	0.20^{***}	0.18^{***}	0.16^{***}	0.12^{***}	0.06^{***}	0.10^{***}
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
% Unemployed (2000)	-0.05	-0.00	-0.06	-0.01	0.11^{*}	0.13^{*}
	(0.05)	(0.03)	(0.07)	(0.02)	(0.04)	(0.06)
% Security (2000)	-0.07^{**}	-0.12^{***}	-0.07^{***}	-0.06^{***}	-0.04^{*}	-0.05^{***}
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
% Own Home (2000)	-0.16^{***}	-0.15^{***}	-0.14^{***}	-0.09^{***}	-0.13^{***}	-0.12^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
% 55+ (2000)	-0.08^{**}	-0.04^{*}	-0.03	-0.01	-0.08^{***}	-0.03
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
% Latino (2000)	-0.05	-0.04^{*}	-0.09^{***}	-0.03^{***}	-0.06^{***}	0.04^{*}
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
% Black (2000)	0.06	-0.00	0.04	0.03^{***}	0.15^{***}	0.24^{***}
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
% Asian (2000)	0.05^{***}	0.01	-0.01	0.01^{**}	-0.03^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Total Pop. (2000)	0.04	0.02	-0.01	-0.01	-0.02	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Pop. Dens. (2000)	0.11^{***}	0.07^{***}	0.04	0.03^{**}	0.09^{***}	0.12^{***}
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
% Democrat (2004)	0.60^{***}	0.55^{***}	0.56^{***}	0.45^{***}	0.40^{***}	0.65^{***}
	(0.05)	(0.03)	(0.04)	(0.01)	(0.03)	(0.03)
R^2	0.65	0.67	0.66	0.79	0.79	0.90
N	2911	2905	2904	2852	2537	2901

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All socio-economic and demographic covariates are from the 2000 census while % of precinct voters registered Democrat is from the California Statewide Database. The reason 2000 covariates are used in these models on the influence of LASD is to prevent post-treatment adjustments. All covariates rescaled between 0-1. HC2 robust standard errors in parentheses.

C.1.3 LASD Model (Long Beach + LA)

Table C3: Relationship between LASD jurisdiction and support for Measure J (Long Beach and Los Angeles + LASD Sample)

	% Measure J	
LASD	-0.15^{***}	-0.03^{***}
	(0.01)	(0.00)
MHHI		-0.04
		(0.03)
% College		0.20^{***}
		(0.02)
% Unemployed		0.04
		(0.03)
% Security		-0.01
		(0.02)
% Own Home		-0.13^{***}
		(0.02)
% 55+		-0.16^{***}
		(0.04)
% Latino		0.01
		(0.02)
% Black		0.07^{*}
		(0.03)
% Asian		0.08^{***}
		(0.01)
Total Pop.		0.03
		(0.02)
Pop. Dens.		0.13^{*}
		(0.06)
% Democrat		0.72^{***}
		(0.04)
Stops Per Capita		0.00
		(0.00)
R^2	0.24	0.75
N	2199	2199

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.1.4 Police Killing Main Results

Table C4: Association Between Exposure to Police Killings and Support For Measure J

	% Measure J			
Exposure	1.59***	0.20*	0.73***	−0.02
	(0.11)	(0.08)	(0.13)	(0.04)
MHHI		−0.04		−0.01
		(0.04)		(0.04)
% College		0.18***		0.18***
		(0.03)		(0.04)
% Unemployed		0.01		0.07
		(0.03)		(0.05)
% Security		−0.05**		0.01
		(0.02)		(0.02)
% Own Home		−0.16***		−0.10***
		(0.02)		(0.03)
% 55+		−0.10**		−0.15**
		(0.03)		(0.05)
% Latino		−0.01		0.02
		(0.03)		(0.04)
% Black		0.05		0.15**
		(0.04)		(0.05)
% Asian		0.03		0.08***
		(0.02)		(0.02)
Total Pop.		0.01		0.02
		(0.03)		(0.03)
Pop. Dens.		0.11*		0.44***
		(0.05)		(0.13)
% Democrat		0.75***		0.62***
		(0.07)		(0.07)
R^2	0.11	0.65	0.18	0.67
N	2037	2037	982	982
Jurisdiction	MPD	MPD	LASD	LASD

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All covariates rescaled between 0-1. Models 1-2 characterize the association between exposure to police killings and support for Measure J for MPD precincts. Models 3-4 do the same for LASD precincts. HC2 robust standard errors in parentheses.

C.1.5 Alternative Exposure Windows

Table C5: Alternative Temporal Exposure Windows

	% Measure J							
Exposure (1 Year)	0.15***				−0.01			
	(0.04)				(0.04)			
Exposure (3 Year)		0.21**				−0.02		
		(0.07)				(0.04)		
Exposure (5 Year)			0.18				−0.04	
			(0.09)				(0.04)	
Exposure (10 Year)				0.44***				−0.01
				(0.12)				(0.05)
MHHI	−0.04	−0.04	−0.04	−0.04	−0.01	−0.01	−0.01	−0.01
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
% College	0.18***	0.18***	0.18***	0.18***	0.17***	0.17***	0.18***	0.17***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
% Unemployed	0.02	0.02	0.02	0.02	0.07	0.07	0.07	0.07
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
% Security	−0.05**	−0.05**	−0.05**	−0.05**	0.00	0.00	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
% Own Home	−0.16***	−0.16***	−0.16***	−0.16***	−0.09***	−0.09***	−0.09**	−0.09**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
% 55+	−0.10**	−0.10**	−0.10**	−0.10**	−0.14**	−0.14**	−0.14**	−0.14**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
% Latino	−0.01	−0.01	−0.01	−0.01	0.02	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
% Black	0.05	0.05	0.06	0.05	0.16***	0.16***	0.16***	0.16***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
% Asian	0.02	0.03	0.04*	0.03	0.07***	0.07***	0.07***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Pop. Dens.	0.09	0.10*	0.10*	0.10	0.44***	0.44***	0.45***	0.44**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.13)	(0.13)
% Democrat	0.73***	0.74***	0.75***	0.74***	0.59***	0.60***	0.60***	0.59***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
R^2	0.65	0.65	0.65	0.65	0.67	0.67	0.67	0.67
N	2037	2037	2037	2037	982	982	982	982
Jurisdiction	MPD	MPD	MPD	MPD	LASD	LASD	LASD	LASD

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Models 1-4 and 5-8 characterize the association between exposure to police killings that have occurred 1, 3, 5, and 10 years prior to the 2020 General Election and support for Measure J. Models 1-4 characterize the association between exposure to police killings and support for Measure J for MPD precincts and Models 5-8 do the same for LASD precincts. HC2 robust standard errors in parentheses.

C.1.6 Covariate Imbalance

Table C6: Assessing Covariate Balance

	MHHI	% College	% Unemployed	% Security	% Own Home	% 55+	% Latino	% Black	% Asian	Total Pop.	Pop. Dens.	% Democrat
Exposure	-1.35^{***}	-2.32^{***}	0.49^{***}	0.75^{***}	-2.32^{***}	-0.83^{***}	3.23^{***}	1.06^{***}	-0.26^{*}	0.58^{***}	0.72^{***}	1.57^{***}
	(0.18)	(0.19)	(0.06)	(0.10)	(0.23)	(0.10)	(0.19)	(0.08)	(0.11)	(0.10)	(0.05)	(0.08)
R^2	0.04	0.07	0.03	0.03	0.06	0.04	0.09	0.04	0.00	0.02	0.08	0.16
N	2037	2037	2037	2037	2037	2037	2037	2037	2037	2037	2037	2037

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. HC2 robust standard errors.

C.2 Notes On Alternative Criminal Justice Ballot Measures

C.2.1 Proposition 57 (2016)

Proposition 57 was considered during the November 8, 2016 General Election throughout California. It is also known as the California Parole for Non-Violent Criminals and Juvenile Court Trial Requirements Initiative. It was approved by California voters with a 64% "yes" vote. A "yes" vote supported increasing parole and good behavior opportunities for felons convicted of nonviolent crimes and allowing judge, not prosecutors, to decide whether to try certain juveniles as adults in court. A "no" vote opposed this measure increasing parole and good behavior opportunities for felons convicted of nonviolent crimes and favored keeping the current system of having prosecutors decide whether to try certain juveniles as adults in court. See `https://ballotpedia.org/California_Proposition_57,_Parole_for_Non-Violent_Criminals_and_Juvenile_Court_Trial_Requirements_(2016)` for more details.

C.2.2 Proposition 47 (2014)

Proposition 47 was considered during the November 4, 2014 Midterm Election throughout California. It is also known as the Reduced Penalties for Some Crimes Initiative. It was approved by California voters with a 60% "yes" vote. A "yes" vote supported classifying certain crimes as misdemeanors instead of felonies unless the defendant had prior convictions for murder, rape, certain sex offenses or certain gun crimes; allowing re-sentencing for those currently serving a prison sentence for any of the offenses that the initiative reduced to misdemeanors; and creating the Safe Neighborhoods and Schools Fund to receive appropriations based on savings from the initiative. A "no" vote opposed the measure. See `https://ballotpedia.org/California_Proposition_47,_Reduced_Penalties_for_Some_Crimes_Initiative_(2014)` for more details.

C.2.3 Proposition 36 (2012)

Proposition 36 was considered during the November 6, 2012 General Election throughout California. It is also known as the Changes to Three Strikes Sentencing Initiative. It was approved by California voters with a 69% "yes" vote. A "yes" vote supported changing the three strikes sentencing system established by a 1994 ballot initiative, Proposition 184, to impose life sentences when new felony convictions are serious or violent; allowed re-sentencing for convicts serving life sentences for felonies that were not serious or violent, except in the case of rape, murder, or child molestation. A "no" vote opposed the measure. See `https://ballotpedia.org/California_Proposition_36,_Changes_to_Three_Strikes_Sentencing_Initiative_(2012)` for more details.

C.2.4 Proposition 5 (2008)

Proposition 5 was considered during the November 4, 2008 General Election throughout California. It is also known as the Nonviolent Drug Offender Sentences and Rehabilitation Initiative. It was disapproved by California voters with a 59% "no" vote. A "yes" vote supported the ballot measure to expand drug treatment programs for criminal offenders, increase prison and parole rehabilitation programs, and reduce penalties for certain marijuana possession crimes. A "no" vote opposed the measure. See `https://ballotpedia.org/California_Proposition_5,_Nonviolent_Drug_Offender_Sentences_and_Rehabilitation_Initiative_(2008)` for more details.

C.2.5 Proposition 66 (2004)

Proposition 66 was considered during the November 2, 2004 General Election throughout California. It is also known as the Changes to Three Strikes Criminal Sentencing Law Initiative. It was disapproved by California voters with a 52% "no" vote. A "yes" vote supported amending the state's three-strikes criminal sentencing law to reduce the number of crimes for which someone can be sentenced for life. A "no" vote opposed the amendment. See https://ballotpedia.org/California_Proposition_66,_Changes_to_Three_Strikes_Criminal_Sentencing_Law_Initiative_(2004) for more details.

C.3 Balance on Policing Intensity by Jurisdiction

C.3.1 Notes on Incorporating Police Stop Data

To generate measures of police intensity across LASD, Long Beach PD, and Los Angeles PD served precincts, we acquired data on LASD contact with civilians (i.e. pedestrian and vehicular stops) from the Sheriff's Automated Contact Reporting System (SACR) website: `https://lasd.org/SACR_opendata.html`. For all stop datasets across LASD, LBPD and LAPD served precincts, we subset the stop data to 2019 since that is the year where police stop data across all three departments temporally overlap. The LASD contact data included information on the street address of each contact. We then geocoded each street address to its latitude/longitude coordinate using the Google Maps API. Then, we identified the geographic intersection of each LASD contact and the 3,019 LAC precincts in our sample. We summed up the number of LASD contacts in each precinct for the year 2019 to determine the number of LASD stops in each precinct. We then normalized the number of LASD stops by the precinct population using information from the 2019 ACS 5-year sample.

We also use data on vehicular and pedestrian stops from the Los Angeles Open Data website: `https://data.lacity.org/Public-Safety/Vehicle-and-Pedestrian-Stop-Data-2010-to-Present/ci25-wgt7`. We merge this data with reporting district shapefiles that determine police patrol and 911 reporting boundaries (see: `https://data.lacounty.gov/GIS-Data/Reporting-Districts/kvwy-dqs6`). We then use a spatial weighted merge between reporting district and LAC election precinct shapefiles to derive estimates of the number of stops in each Los Angeles city election precinct during the year 2019. We normalize the number of LAPD stops by the precinct population in 2019.

Finally, we use vehicular and pedestrian stop data from the Long Beach Open Data website: `https://datalb.longbeach.gov/datasets/3d57257946ab46908440f0daa134043c_0/explore`. The data include street address information, which we geocode using the Google Maps API to gather latitude/longitude coordinates of each LBPD traffic/pedestrian stop. We identify the geographic intersection of each LBPD stop with the 3,019 LAC precincts in our sample. We sum up the number of LBPD stops in each precinct for the year 2019 to determine the number of LBPD stops in each precinct. We then normalize the number of LBPD stops by the 2019 precinct population.

C.3.2 Balance Test of Policing Intensity

Table C7: The intensity of policing is balanced between LASD and MPD regions

	Stops per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
LASD	0.07	0.21	0.06	0.31	0.43	0.29
	(0.18)	(0.18)	(0.18)	(0.41)	(0.41)	(0.41)
Outcome SD	3.71	5.19	3.82	7.01	8.12	7.19
Border	N	N	N	Y	Y	Y
Sample	LA, LB, LASD	LB, LASD	LA, LASD	LA, LB, LASD	LB, LASD	LA, LASD
R^2	0.00	0.00	0.00	0.00	0.00	0.00
N	2199	1111	2070	607	453	578

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Models 1-3 and 4-6 use a) LA, LB and LASD, b) LB, LASD, and c) LA, LASD precinct samples respectively. Models 1-3 use all precincts in LA, LB, and LASD. Models 4-6 use all precincts bordering LASD jurisdiction from LA, LB, and LASD (see Section **??**. HC2 robust standard errors in parentheses.

C.4 Alternative Exposure Measures

Table C8: Association between exposure to police killings and support for Measure J using alternative measurement

	% Measure J	
	(1)	(2)
Exposure (2)	0.01	
	(0.01)	
Exposure (3)	0.01	
	(0.01)	
Exposure (4)	$0.01^{\dagger}$	
	(0.01)	
Log(Exposure)		$0.05^{\dagger}$
		(0.03)
R^2	0.65	0.65
N	2037	2037
Demographic Controls	Y	Y
Socio-Economic Controls	Y	Y
Political Controls	Y	Y

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. All models are fully specified with the inclusion of demographic, socio-economic, and political covariates. Model 1 assesses the association between binary quartiles of the original exposure (higher value quartiles = closer to police killing) and support for Measure J. Model 2 assesses the association between logged exposure and support for Measure J. Given the original exposure measure is negatively signed (between -1 to 0), logged exposure is equal to $log(exposure \times -1) * -1$. All covariates re-scaled between 0-1. HC2 robust standard errors in parentheses.

C.5 Alternative Specifications

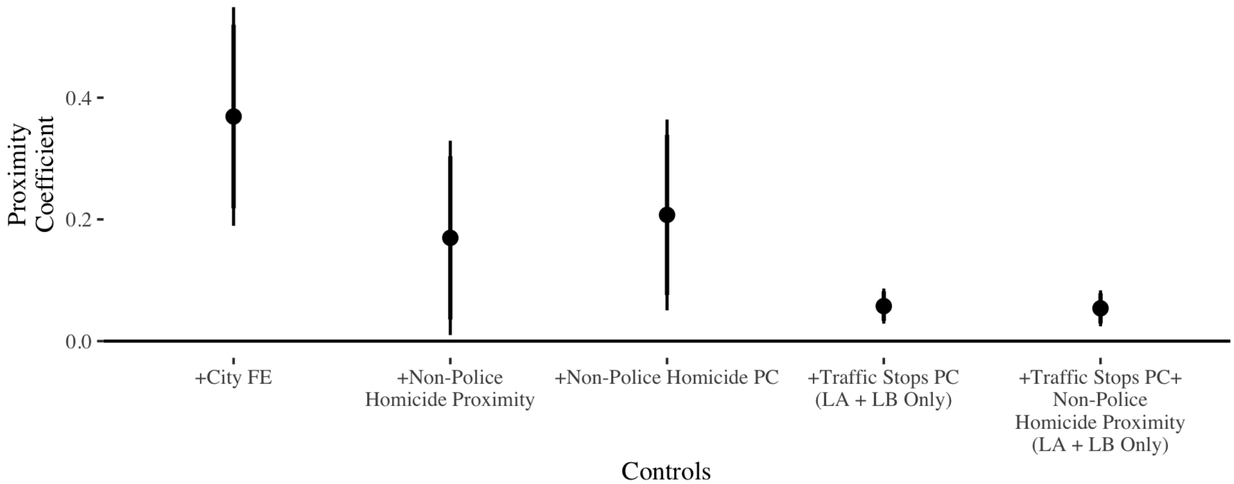

Figure C10: Association Between Exposure to Police Killings and Support for Measure J with the Inclusion of Alternative Control Covariates in MPD Precincts. From left to right, the models include covariates for city fixed effects, proximity to the nearest non-police homicide, the number of non-police homicides per capita within each precinct, the number of traffic stops per capita (LA and Long Beach precincts only), the number of traffic stops per capita in addition to proximity to non-police homicides (LA and Long Beach precincts only). 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

C.5.1 Measuring Stops

To adjust for alternative sources of policing beyond police killings, we use data on vehicular stops in the 10 years prior to the 2020 General election from the Los Angeles and Long Beach open data websites (see `https://data.lacity.org/Public-Safety/Vehicle-and-Pedestrian-Stop-Dat ci25-wgt7` and `https://datalb.longbeach.gov/datasets/3d57257946ab46908440f0daa134043c_0/explore`). Los Angeles stop data is at the reporting district level, which determines police patrol and 911 reporting boundaries. We use a spatial weighed merge between reporting district and LAC election precinct shapefiles to derive estimates of the number of vehicular stops in each Los Angeles city election precinct in the 10 years prior to the 2020 General Election. We normalize the number of LAPD vehicular stops by the precinct population in 2019. The Long Beach vehicular stop data include street address information for each stop, which we geocode using the Google Maps API to gather latitude/longitude coordinates of each LBPD traffic stop. We identify the geographic intersection of each LBPD stop with the 3,019 LAC precincts in our sample. We sum up the number of LBPD stops in each precinct for the 10 years prior to the 2020 General Election to determine the number of LBPD stops in each precinct. We then normalize the number of LBPD stops by the 2019 precinct population.

C.5.2 Alternative Specification Regression Tables

Table C9: Association Between Exposure to Police Killings and Support For Measure J (Alternative Specifications)

	% Measure J				
	(1)	(2)	(3)	(4)	(5)
Police Killing Exposure	0.35***	0.16*	0.20*	0.05***	0.05***
	(0.09)	(0.08)	(0.08)	(0.01)	(0.02)
Homicide Exposure		0.00*			−0.03**
		(0.00)			(0.01)
Homicides Per Capita			0.00		
			(0.00)		
Stops Per Capita				−0.01	−0.01*
				(0.01)	(0.01)
MHHI	−0.01	−0.04	−0.04	−0.00	−0.00
	(0.04)	(0.04)	(0.04)	(0.00)	(0.00)
% College	0.16***	0.19***	0.18***	0.00***	0.00***
	(0.03)	(0.03)	(0.03)	(0.00)	(0.00)
% Unemployed	0.02	0.02	0.01	0.00*	0.00
	(0.03)	(0.03)	(0.03)	(0.00)	(0.00)
% Security	−0.03	−0.05**	−0.05**	−0.00**	−0.00**
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)
% Own Home	−0.16***	−0.16***	−0.16***	−0.17***	−0.17***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
% 55+	−0.07*	−0.10**	−0.10**	−0.00*	−0.00*
	(0.03)	(0.03)	(0.03)	(0.00)	(0.00)
% Latino	0.01	−0.01	−0.01	0.07	0.04
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
% Black	0.05	0.06	0.06	0.10	0.09
	(0.05)	(0.04)	(0.04)	(0.07)	(0.07)
% Asian	0.07**	0.03	0.04	0.12***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Pop. Dens.	0.06	0.10	0.10*	0.00	−0.00
	(0.05)	(0.05)	(0.05)	(0.00)	(0.00)
% Democrat	0.67***	0.73***	0.75***	0.69***	0.67***
	(0.10)	(0.08)	(0.07)	(0.13)	(0.14)
R^2	0.70	0.65	0.65	0.68	0.68
N	2037	2037	2037	1217	1217
City FE	Y	N	N	N	N
Sample	All MPD	All MPD	All MPD	LB + LA	LB + LA

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Models 1-3 use all MPD served precincts in the analysis. Models 4-5 use only Long Beach and Los Angeles electoral precincts. Model 1 adjusts for city fixed effects. Models 2 and 5 adjust for exposure to non-police homicides in the 4 years prior to the 2020 General Election. Model 3 adjusts for homicides per capita in the 4 years prior to the 2020 General Election. Models 4-5 adjust for traffic stops per capita at the precinct-level imposed by the Los Angeles and Long Beach police departments. All covariates rescaled between 0-1. HC2 robust standard errors in parentheses.

C.5.3 Adjusting for % Registered Democrat in 2020

Table C10: Bivariate Relationship between LASD jurisdiction and support for Measure J (Adjusting for 2020 % Democrat)

	% Measure J	% Measure J
LASD	-0.11^{***}	-0.02^{***}
	(0.01)	(0.00)
MHHI		-0.03
		(0.03)
% College		0.11^{***}
		(0.02)
% Unemployed		0.04
		(0.02)
% Security		-0.03
		(0.02)
% Own Home		-0.14^{***}
		(0.01)
% 55+		-0.12^{***}
		(0.02)
% Latino		-0.02
		(0.02)
% Black		0.10^{**}
		(0.03)
% Asian		0.04^{***}
		(0.01)
Total Pop.		-0.01
		(0.02)
Pop. Dens.		0.14^{**}
		(0.05)
% Democrat (2020)		0.76^{***}
		(0.06)
R^2	0.12	0.74
Num. obs.	3019	3019

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.6 Alternative Police Killing Measures

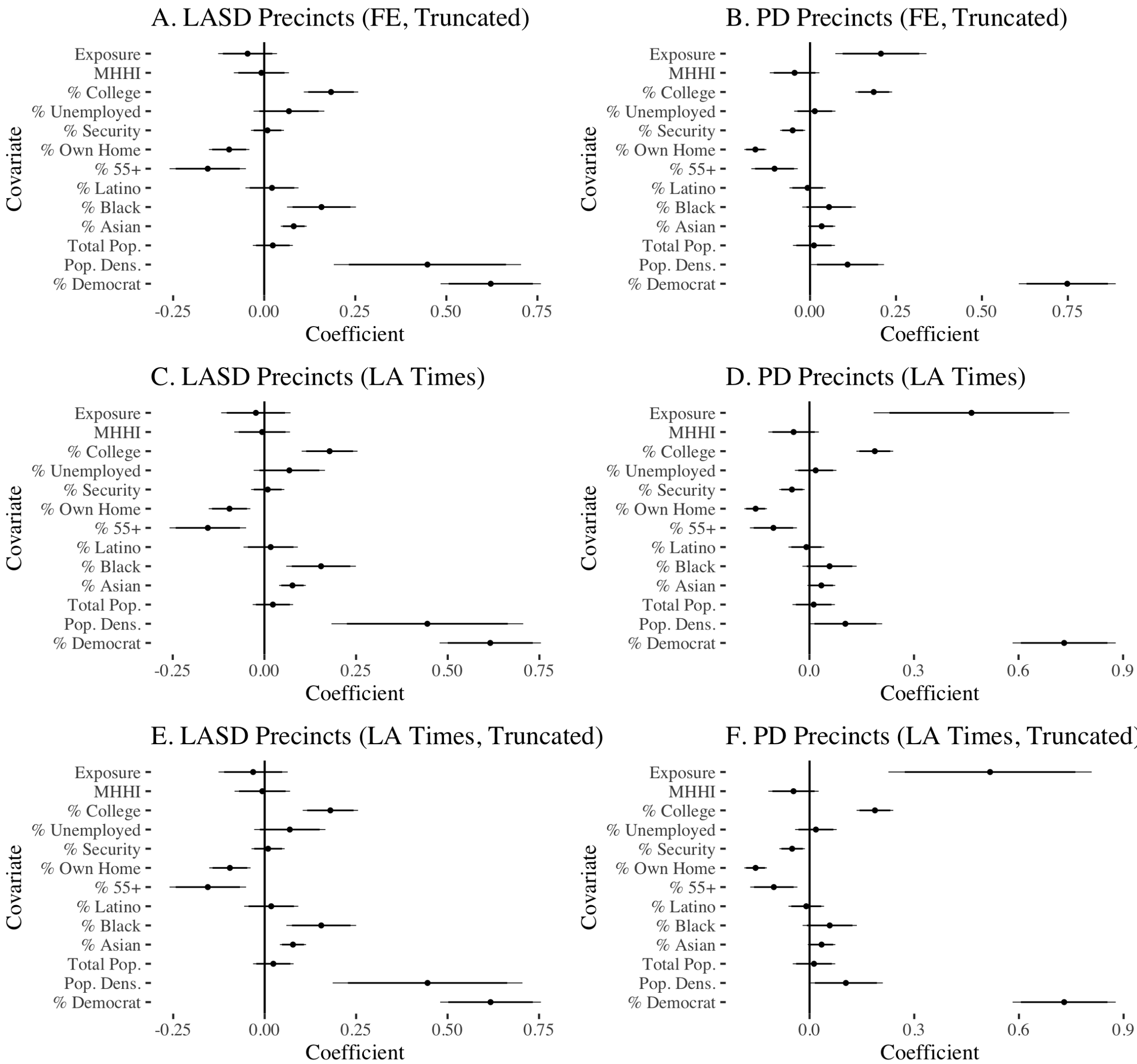

Figure C11: Association Between Exposure to Police Killings and Support for Measure J Using Alternative Measures of Police Killings. Panels A-B truncate the Fatal Encounters police killing measure by excluding police killings that are not the result of a gunshot, taser, asphyxiation, or beating. Panels C-D use police killings from the LA Times police homicide database. Panels E-F use police killings from the LA Times police homicide database but excluding murders of bystanders or suicides in the presence of police. Panels A, C and E characterize the association between police killings and support for Measure J in LASD precincts. Panels B, D and F characterize the association between police killings and support for Measure J in non-LASD precincts. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

C.7 Police Killing Characteristics Are Balanced Between LASD/MPD

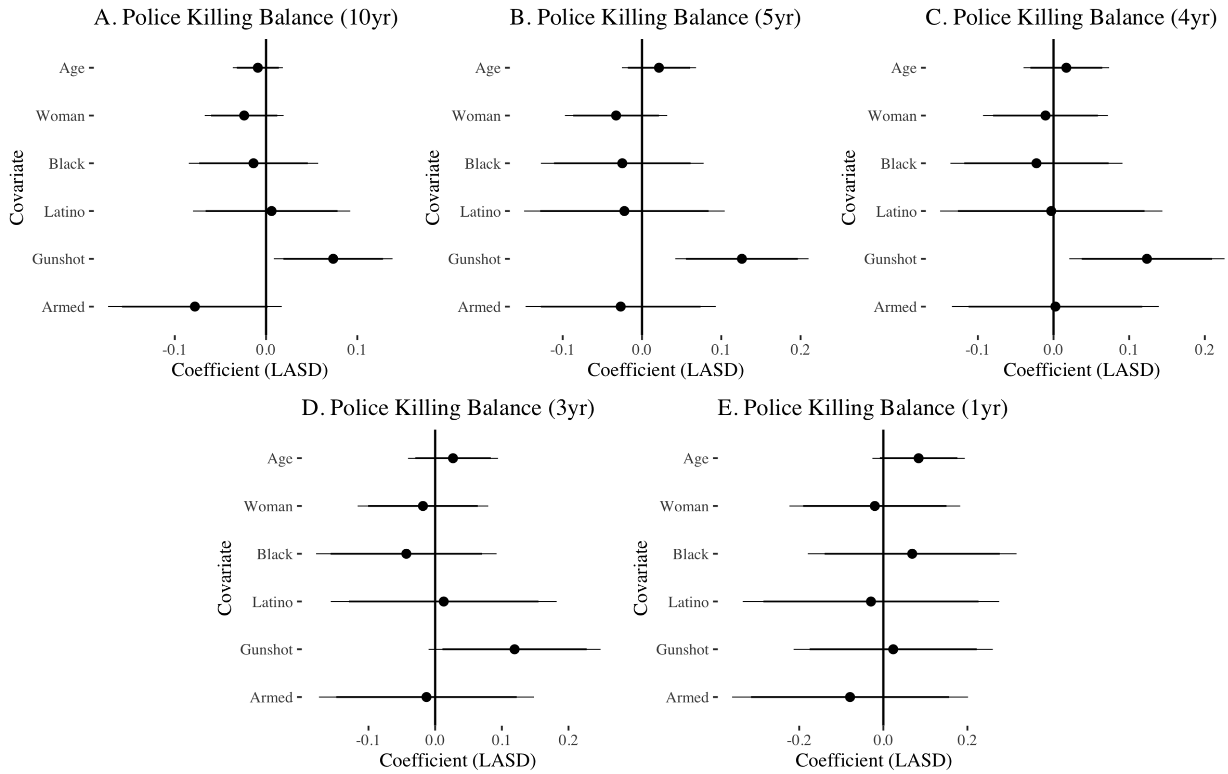

Figure C12: The Characteristics of Police Killings That Occur In MPD and LASD Regions Are Similar. Panels A, B, C and D compare LASD and MPD police killings in the past 10, 5, 4, 3, and 1 year(s). The x-axis is the LASD coefficient. The y-axis is the police killing characteristic (i.e. age, woman, Black, Latino, gunshot, if the individual was armed).

C.8 Police Killing Placebo Test

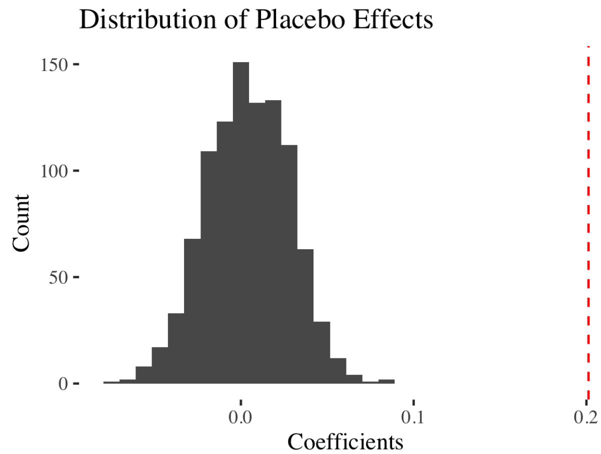

Figure C13: Distribution of Placebo Coefficients Characterizing the Association Between Proximity to Randomly Distributed "Fake" Police Killing Events and Support for Measure J (1000 simulations, Adjusting for a Full Set of Control Covariates). Y-axis is the count of coefficients. X-axis is the size of coefficients. Black vertical line characterizes the true coefficient characterizing the association between proximity to police killings in the past 4 years and support for Measure J. To conduct this analysis, we assign 253 random points to the geographic space that constitutes LAC. We choose 253 random points because there were 253 police killings that occurred in the 4 years prior to the 2020 Election.

C.9 Disaggregation by Race of Subject

Figure C14: Coefficients Characterizing Influence of Police Killings in the 4 Years Prior to the 2020 General Election on Support for Measure J (y-axis) in non-LASD Precincts Disaggregating by Race of Subject (x-axis). Each coefficient is derived from a different regression model swapping different measures of police killing exposure by race of subject. All estimates are based on fully specified models. 95% confidence intervals displayed derived from HC2 robust standard errors.

C.10 Beta Regression

C.10.1 Influence of LASD Service

Table C11: Bivariate Relationship between LASD jurisdiction and support for Measure J (Using Beta Regression)

	% Measure J	
LASD	-0.58^{***}	-0.13^{***}
	(0.04)	(0.04)
MHHI		1.16^{***}
		(0.21)
% College		0.45^{**}
		(0.17)
% Unemployed		-0.15
		(0.22)
% Security		0.19
		(0.13)
% Own Home		-0.73^{***}
		(0.11)
% 55+		-1.28^{***}
		(0.22)
% Latino		-0.32^{*}
		(0.15)
% Black		-0.07
		(0.19)
% Asian		0.43^{***}
		(0.12)
Total Pop.		0.86^{***}
		(0.12)
Pop. Dens.		0.42
		(0.34)
% Democrat		3.94^{***}
		(0.21)
Pseudo R^2	0.02	0.11
Log Likelihood	302.62	900.64
N	3019	3019

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.10.2 Police Killing Exposure

Table C12: Association Between Exposure to Police Killings and Support for Measure J (Beta Regression Models)

	LASD	MPD
Exposure	-0.01	2.59^{***}
	(0.44)	(0.74)
Demographic Controls	Y	Y
Socio-Economic Controls	Y	Y
Political Controls	Y	Y
Pre-Treatment Exposure	Y	Y
Pseudo R^2	0.15	0.06
Log Likelihood	325.91	643.34
N	982	2037

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C.11 Using Full Sample and Assessing Heterogeneity

Table C13: Heterogenous influence of exposure to police killings conditional on LASD jurisdiction

	% Measure J
Exposure x LASD	-0.23^{*}
	(0.09)
Exposure	0.21^{**}
	(0.08)
LASD	-0.03^{***}
	(0.00)
Demographic Controls	Y
Socio-Economic Controls	Y
Political Controls	Y
R^2	0.69
N	3019

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. HC2 robust standard errors in parentheses.

C.12 Accounting for Abstention

C.12.1 LASD Analysis Including Abstainers in Denominator

Table C14: Association Between LASD Jurisdiction and support for Measure J (Measure J Abstainers Included in Measure J Denominator)

	% Measure J	
LASD	-0.10^{***}	-0.02^{***}
	(0.01)	(0.00)
MHHI		-0.03
		(0.03)
% College		0.19^{***}
		(0.02)
% Unemployed		0.02
		(0.03)
% Security		-0.01
		(0.01)
% Own Home		-0.12^{***}
		(0.01)
% 55+		-0.15^{***}
		(0.03)
% Latino		0.02
		(0.02)
% Black		0.07^{**}
		(0.02)
% Asian		0.01
		(0.01)
Total Pop.		0.01
		(0.02)
Pop. Dens.		0.12^{*}
		(0.05)
% Democrat		0.66^{***}
		(0.03)
R^2	0.11	0.69
N	3019	3019

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All covariates rescaled between 0-1. HC2 robust standard errors in parentheses.

C.12.2 LASD Analysis w/Abstention Rate Outcome

Table C15: Bivariate Relationship between LASD jurisdiction and abstention rate

	% Abstain	
LASD	−0.00	−0.00
	(0.00)	(0.00)
MHHI		0.03*
		(0.01)
% College		−0.07***
		(0.02)
% Unemployed		−0.01
		(0.01)
% Security		−0.01
		(0.01)
% Own Home		−0.02**
		(0.01)
% 55+		0.03*
		(0.02)
% Latino		−0.06***
		(0.01)
% Black		−0.04**
		(0.01)
% Asian		0.07***
		(0.01)
Total Pop.		0.01
		(0.01)
Pop. Dens.		0.02
		(0.02)
% Democrat		−0.00
		(0.01)
R^2	0.00	0.18
N	3019	3019

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All covariates rescaled between 0-1. HC2 robust standard errors in parentheses.

C.12.3 Model-Based Exposure Analysis Including Abstainers in Denominator

Table C16: Association Between Exposure to Police Killings and Support For Measure J

	% Measure J			
Exposure	1.49***	0.21**	0.65***	−0.02
	(0.10)	(0.08)	(0.11)	(0.04)
MHHI		−0.04		−0.01
		(0.04)		(0.03)
% College		0.21***		0.19***
		(0.03)		(0.04)
% Unemployed		0.02		0.07
		(0.03)		(0.05)
% Security		−0.04*		0.01
		(0.02)		(0.02)
% Own Home		−0.13***		−0.09***
		(0.02)		(0.03)
% 55+		−0.11**		−0.15**
		(0.03)		(0.05)
% Latino		0.03		0.04
		(0.03)		(0.03)
% Black		0.06		0.16***
		(0.04)		(0.05)
% Asian		0.01		0.03
		(0.02)		(0.02)
Total Pop.		0.00		0.02
		(0.03)		(0.03)
Pop. Dens.		0.10		0.37**
		(0.05)		(0.11)
% Democrat		0.70***		0.52***
		(0.07)		(0.07)
R^2	0.11	0.64	0.17	0.66
N	2037	2037	982	982

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All covariates rescaled between 0-1. Models 1-2 characterize the association between exposure to police killings and support for Measure J for MPD precincts. Models 3-4 do the same for LASD precincts. HC2 robust standard errors in parentheses.

C.12.4 Model-Based Exposure Analysis w/Abstention Rate Outcome

Table C17: Association Between Exposure to Police Killings and Abstention Rates

	% Abstain			
Exposure	-0.15^{***}	-0.05	0.03	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
MHHI		0.02		0.04
		(0.01)		(0.02)
% College		-0.09^{***}		-0.06^{*}
		(0.02)		(0.03)
% Unemployed		-0.00		-0.03
		(0.01)		(0.03)
% Security		-0.01		-0.01
		(0.01)		(0.01)
% Own Home		-0.02^{***}		-0.01
		(0.01)		(0.01)
% 55+		0.02		0.02
		(0.02)		(0.03)
% Latino		-0.08^{***}		-0.05^{*}
		(0.02)		(0.02)
% Black		-0.03		-0.05
		(0.01)		(0.03)
% Asian		0.05^{***}		0.09^{***}
		(0.01)		(0.01)
Total Pop.		0.01		0.00
		(0.01)		(0.01)
Pop. Dens.		-0.00		0.02
		(0.02)		(0.06)
% Democrat		-0.06^{**}		0.05
		(0.02)		(0.03)
R^2	0.01	0.23	0.00	0.17
N	2037	2037	982	982

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All covariates rescaled between 0-1. Models 1-2 characterize the association between exposure to police killings and abstention rates for MPD precincts. Models 3-4 do the same for LASD precincts. HC2 robust standard errors in parentheses.

D Design Based Approach

D.1 LASD Border Regression Tables

D.1.1 Border Analysis Regression Table: Covariate Imbalance

Table D18: Balance Test Between LASD and Non-LASD Precincts

	MHHI	**% College**	**% Unemployed**	**% Security**	**% Own Home**	**% 55+**	**% Latino**	**% Black**	**% Asian**	**Total Pop.**	**Pop. Dens.**	**% Democrat**	**Exposure**	**Homicides**
Panel A: Full Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
LASD	-0.05^{***}	-0.04^{***}	-0.00	0.03^{**}	0.02^{*}	0.04^{***}	0.02^{***}	-0.00	0.04^{***}	0.19^{***}	-0.06^{***}	-0.06^{***}	-0.01^{*}	0.00
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
R^2	0.03	0.07	0.00	0.00	0.00	0.02	0.01	0.00	0.01	0.10	0.01	0.04	0.00	0.00
N	3019	3019	3019	3019	3019	3019	3019	3019	3019	3019	3019	3019	3019	3019
Panel B: Border Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
LASD	-0.02	0.00	-0.02	0.05^{*}	0.02	0.01	0.02^{*}	0.00	0.00	0.06^{***}	-0.01	-0.01	0.00	0.00
	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)
R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
N	922	922	922	922	922	922	922	922	922	922	922	922	922	922

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Panel A characterizes the association between LASD service provision and baseline covariates using the full sample of LAC precincts. Panel B characterizes the association between LASD service provision and baseline covariates using the sample of LAC precincts bordering LASD jurisdiction. HC2 robust standard errors in parentheses.

D.1.2 Border Analysis Regression Table: Influence of LASD Service

Table D19: Association Between LASD and Support for Measure J Using Bordering Precincts

	% Measure J		
	(1)	(2)	(3)
LASD	-0.02^{***}	-0.02^{*}	$-0.02^{\dagger}$
	(0.00)	(0.01)	(0.01)
MHHI	-0.03		
	(0.03)		
% College	0.18^{***}		
	(0.02)		
% Unemployed	0.02		
	(0.03)		
% Security	-0.02		
	(0.02)		
% Own Home	-0.14^{***}		-0.21^{***}
	(0.01)		(0.02)
% 55+	-0.15^{***}		0.09
	(0.03)		(0.06)
% Latino	-0.02		0.08^{***}
	(0.02)		(0.01)
% Black	0.07^{**}		
	(0.02)		
% Asian	0.05^{***}		
	(0.01)		
Total Pop.	0.02		
	(0.02)		
Pop. Dens.	0.15^{**}		
	(0.05)		
% Democrat	0.74^{***}		
	(0.04)		
R^2	0.70	0.01	0.16
N	3019	922	922
Sample	Full	Border	Border
Controls	Y	N	Y

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. Model 1 characterizes the association between LASD service provision and support for Measure J using the full LAC precinct sample. Model 2 characterizes the association between LASD service provision and support for Measure J using the sample of LAC precincts bordering LASD jurisdiction. Model 3 is the same as Model 2, but adjusts for imbalanced covariates between MPD and LASD precincts along the LASD jurisdiction border identified on Figure 3, Panel B. All covariates rescaled between 0-1. HC2 robust standard errors in parentheses.

D.2 Police Killing Regression Tables

Table D20: Effect of Police Killing Exposure on Support for Measure J (MPD Precincts)

Panel A: No Controls					**% Measure J**				
Exposure	0.03	0.05^{*}	0.06^{*}	0.02	0.05^{**}	0.04^{**}	$0.03^{\dagger}$	0.05^{***}	0.03^{**}
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
R^2	0.05	0.10	0.06	0.02	0.08	0.05	0.03	0.06	0.03
N	26	40	61	62	92	133	106	163	234
Panel B: w/Controls					**% Measure J**				
Exposure	0.02	0.05^{*}	$0.05^{\dagger}$	0.02	0.03^{*}	0.05^{**}	0.02	0.03^{*}	0.03^{***}
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.13	0.10	0.10	0.40	0.28	0.22	0.43	0.42	0.41
N	26	40	61	62	92	133	106	163	234
Distance From Killing		< 0.5 mile			< 0.75 mile			< 1 mile	
Months From Election	± 3	± 4	± 5	± 3	± 4	± 5	± 3	± 4	± 5

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. Panel B includes estimates adjusting for imbalanced control covariates. HC2 robust standard errors in parentheses.

D.3 Police Killing Balance

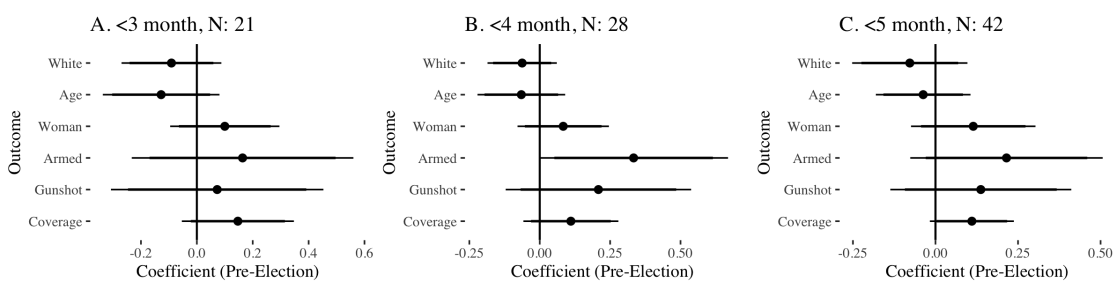

Figure D15: Balance Test on Police Killing Characteristics Before and After the 2020 General Election. X-axis is the coefficient for a pre-election indicator. Y-axis is the police killing outcome of interest. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates re-scaled between 0-1.

D.4 Pre-Treatment Outcome Falsification Test

D.4.1 Proposition 57 (2016)

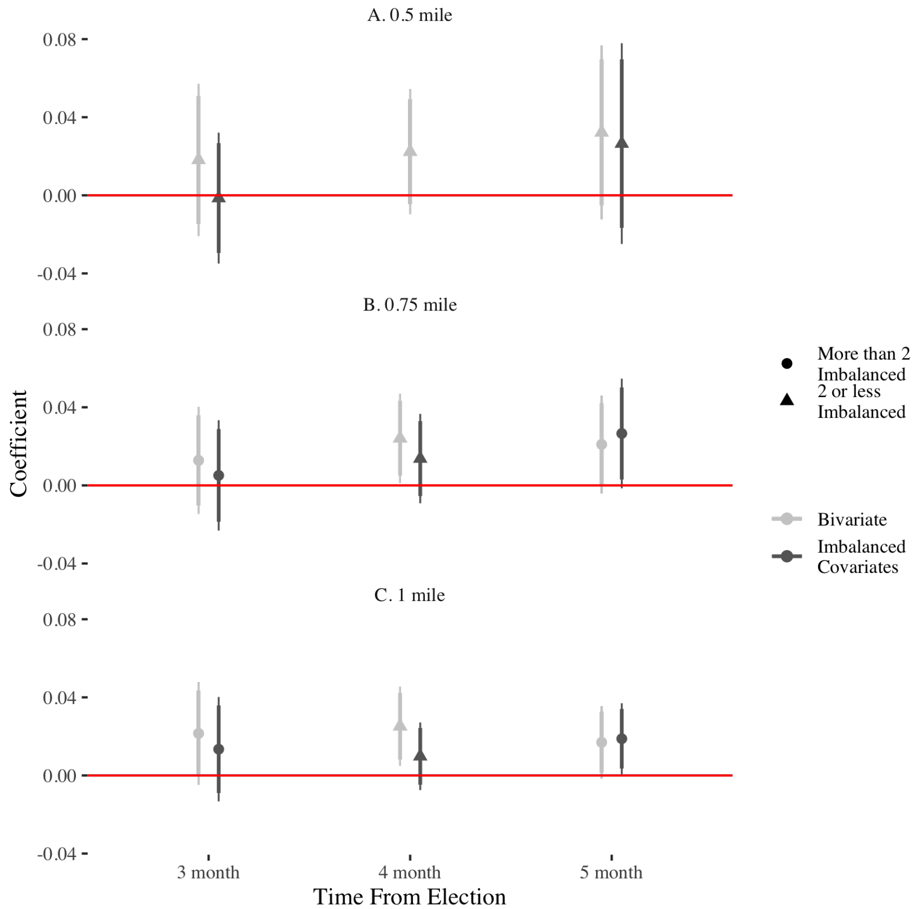

Figure D16: Effect of Police Killings near the 2020 General Election on Support for Proposition 57 (2016). The x-axis is the temporal subset. The y-axis is the coefficient for the effect of police killings. Each panel characterizes different distances from police killings. Color denotes the inclusion/exclusion of control covariates. Shape denotes the degree of imbalance for each set of coefficients. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

D.4.2 Proposition 47 (2014)

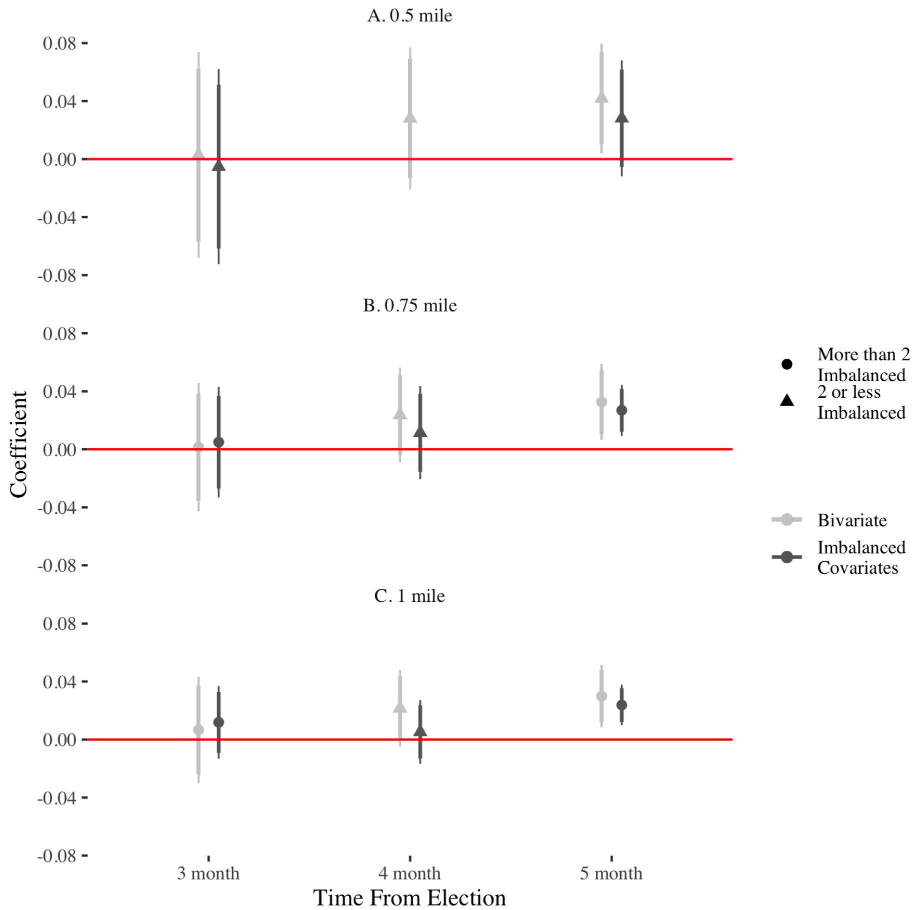

Figure D17: Effect of Police Killings near the 2020 General Election on Support for Proposition 47 (2014). The x-axis is the temporal subset. The y-axis is the coefficient for the effect of police killings. Each panel characterizes different distances from police killings. Color denotes the inclusion/exclusion of control covariates. Shape denotes the degree of imbalance for each set of coefficients. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

D.4.3 Proposition 36 (2012)

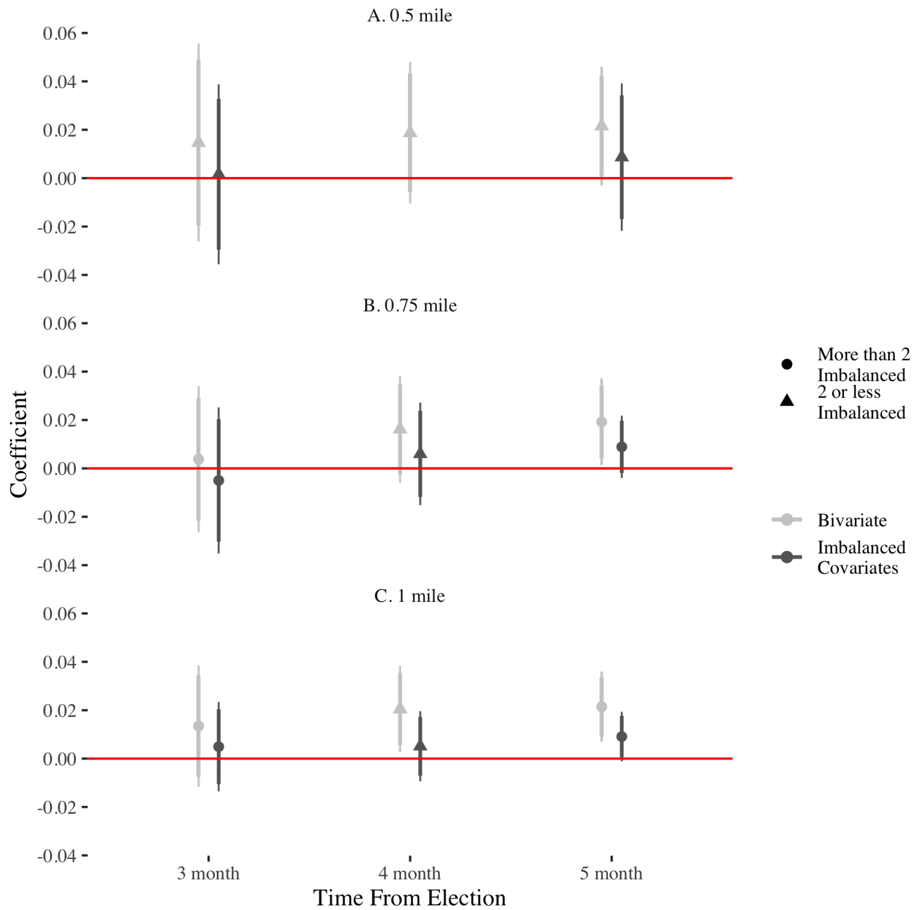

Figure D18: Effect of police killings near the 2020 General Election on Support for Proposition 36 (2012). The x-axis is the temporal subset. The y-axis is the coefficient for the effect of police killings. Each panel characterizes different distances from police killings. Color denotes the inclusion/exclusion of control covariates. Shape denotes the degree of imbalance for each set of coefficients. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

D.4.4 Proposition 5 (2008)

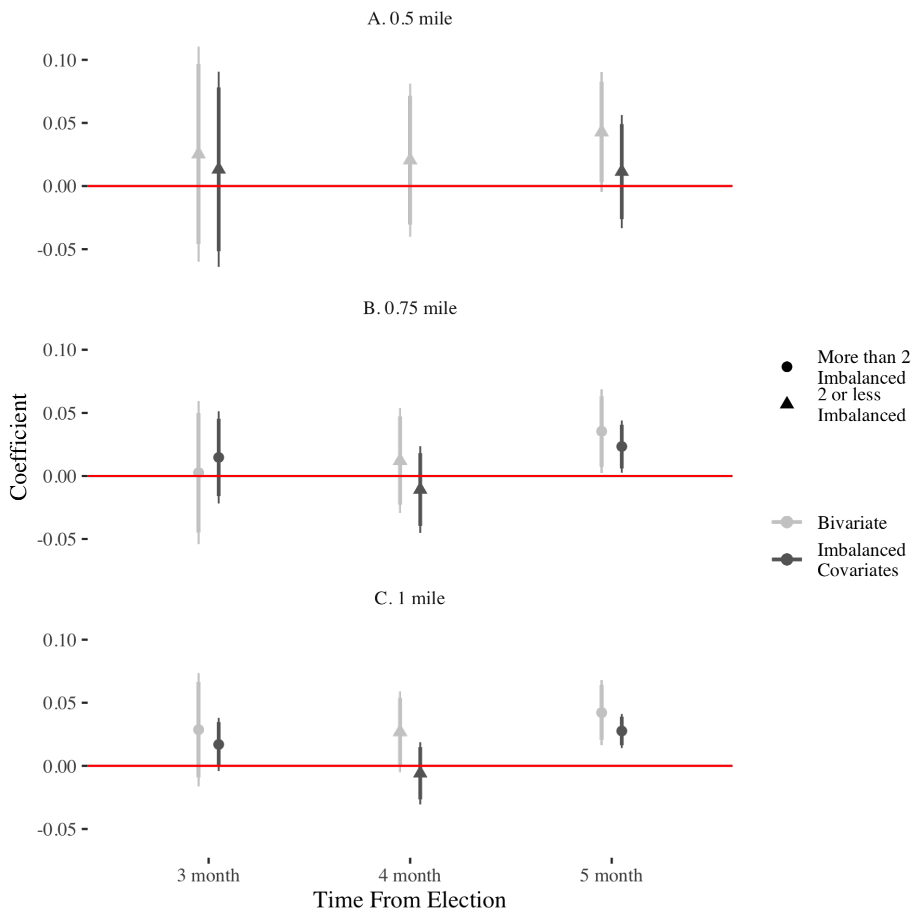

Figure D19: Effect of Police Killings near the 2020 General Election on Support for Proposition 5 (2008). The x-axis is the temporal subset. The y-axis is the coefficient for the effect of police killings. Each panel characterizes different distances from police killings. Color denotes the inclusion/exclusion of control covariates. Shape denotes the degree of imbalance for each set of coefficients. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

D.4.5 Proposition 66 (2004)

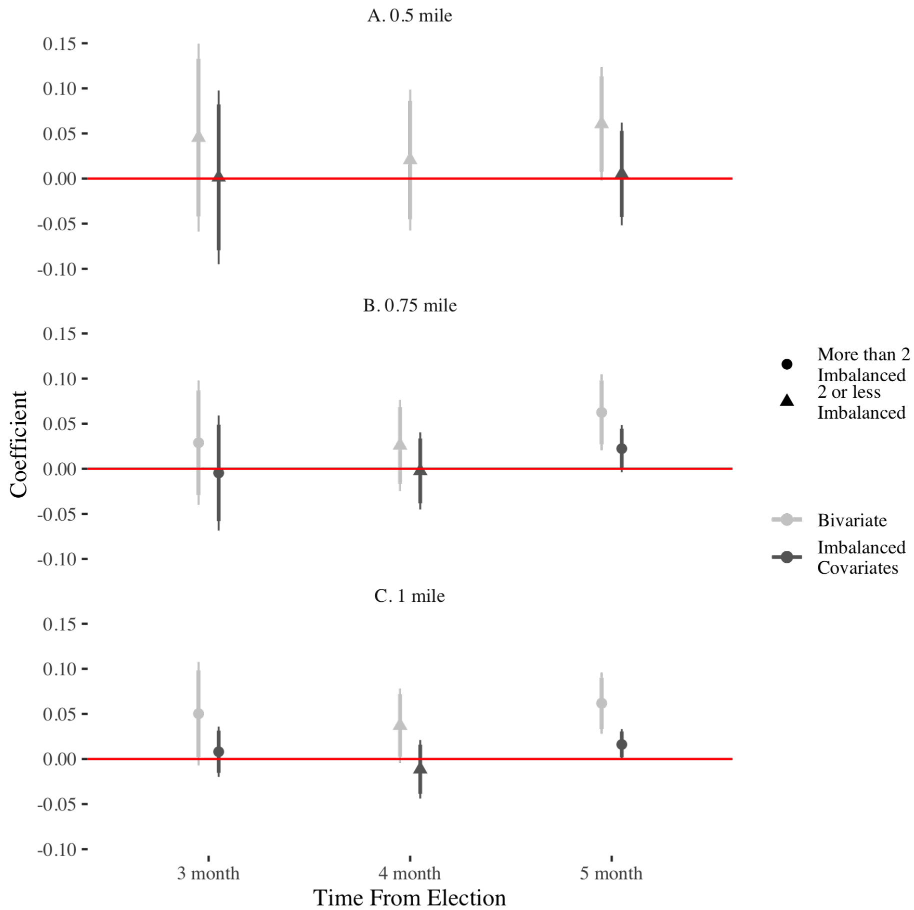

Figure D20: Effect of Police Killings near the 2020 General Election on Support for Proposition 66 (2004). The x-axis is the temporal subset. The y-axis is the coefficient for the effect of police killings. Each panel characterizes different distances from police killings. Color denotes the inclusion/exclusion of control covariates. Shape denotes the degree of imbalance for each set of coefficients. 95% confidence intervals displayed derived from HC2 robust standard errors. All covariates rescaled between 0-1.

D.5 LASD Analysis

D.5.1 Balance Plot

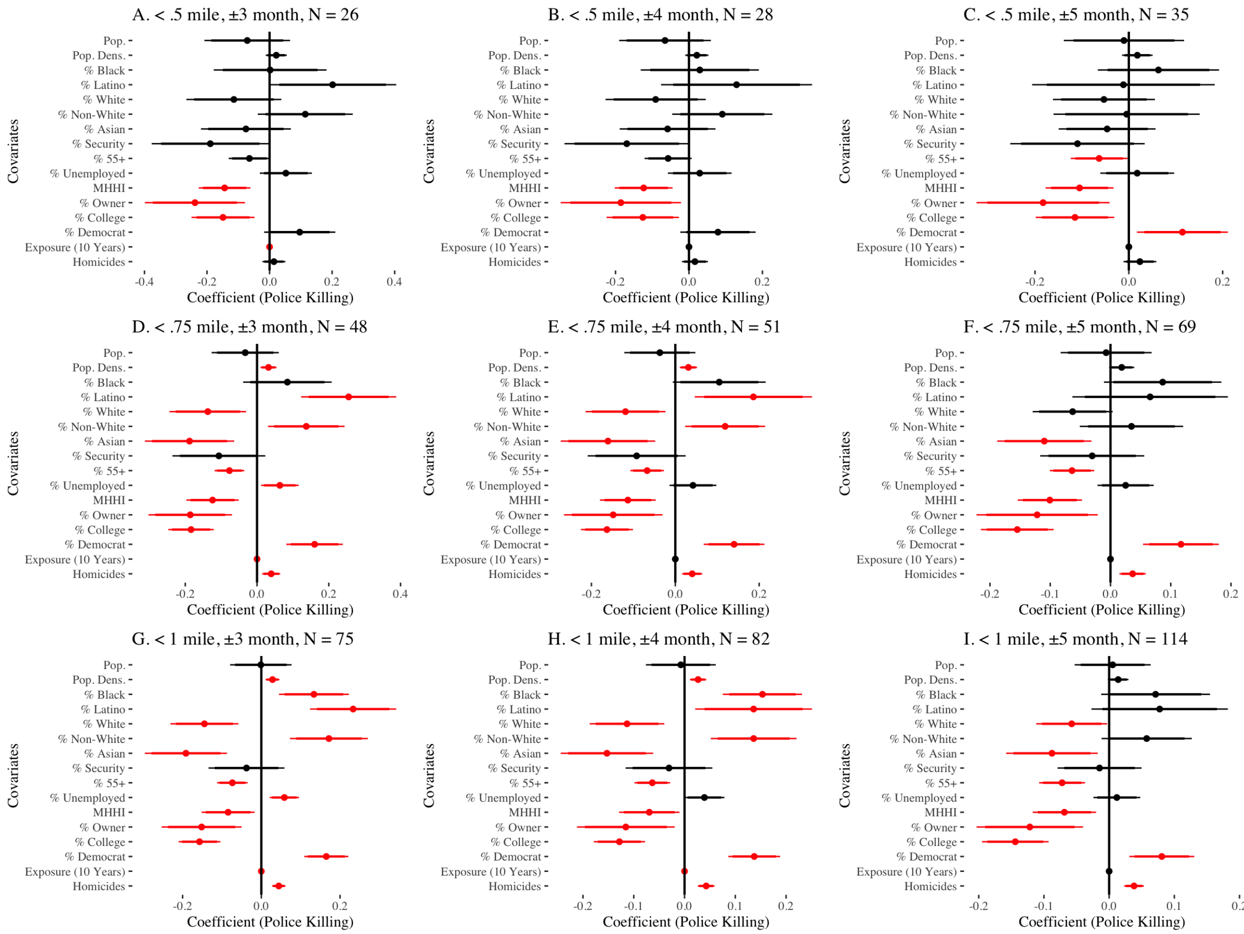

Figure D21: Balance Plot Across Distance-Time Pairings in LASD Precincts. X-axis is coefficient of police killing prior to election. Y-axis is the covariate of interest. The top three, middle three, and bottom three panels characterize balance tests using police killing exposure measures that are 0.5, 0.75 and 1 mile between a police killing and the centroid of a precinct. From left to right, each plot is derived from data 3, 4, and 5 months before and after the election respectively. Sample size for each time/distance pair displayed on each panel title. All covariates scaled between 0-1. Color denotes statistical significance (red = statistically significant, black = otherwise).

D.5.2 Coefficient Plot

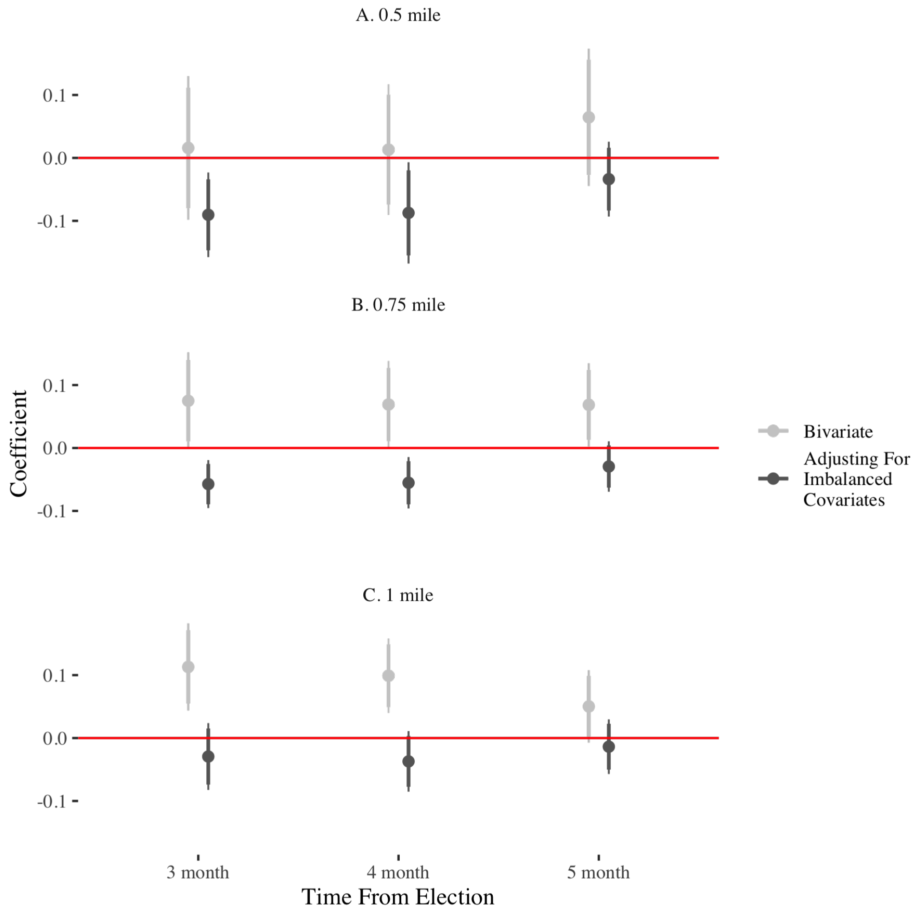

Figure D22: Effect of Police Killings Near Election Time on Support for Measure J in LASD Precincts. The x-axis is the temporal subset. The y-axis is the coefficient for the effect of police killings. Color denotes the inclusion/exclusion of control covariates. Shape denotes the degree of imbalance for each set of coefficients. 95% confidence intervals displayed derived form HC2 robust standard errors. All covariates rescaled between 0-1.

D.6 Homicide Analysis

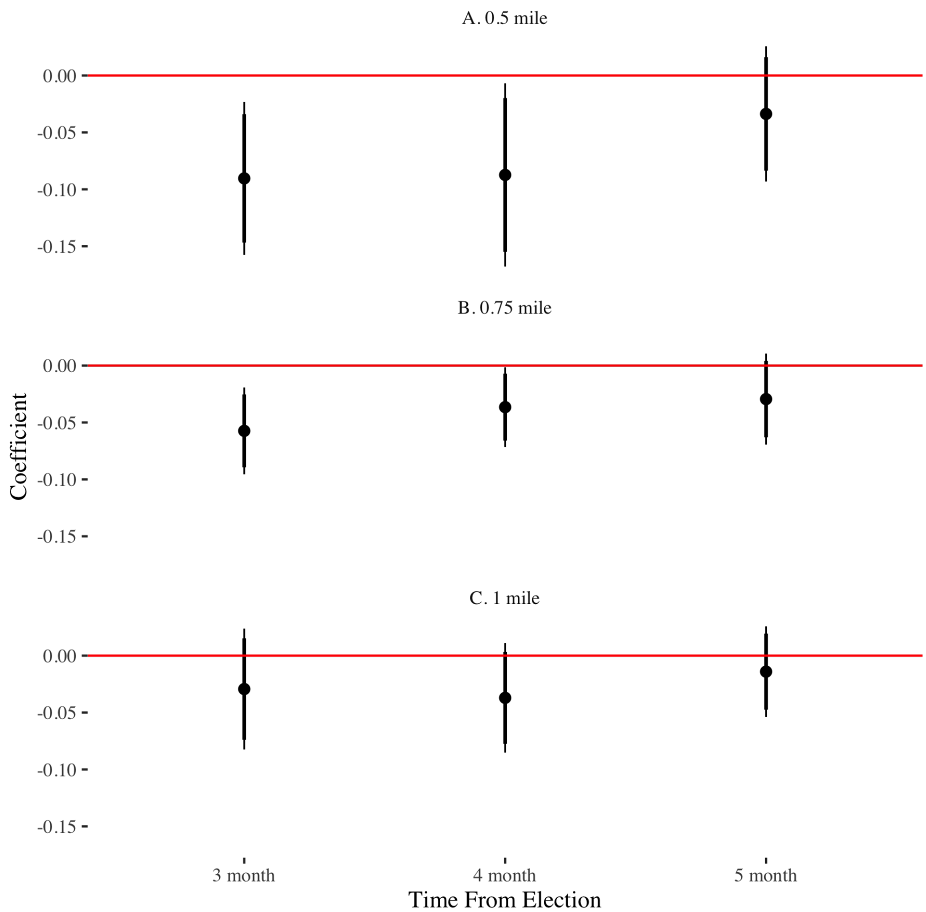

Figure D23: Effect of Homicides That Are Not Police Killings near Election Time on Support for Measure J in MPD Precincts. The x-axis is the temporal subset. The y-axis is the coefficient for the effect of nearby homicide occuring before versus after the election. All estimates are adjusted for imbalanced covariates. 95% confidence intervals displayed derived form HC2 robust standard errors. All covariates rescaled between 0-1.

D.7 Accounting for Abstention

D.7.1 Including Abstainers in Design-Based Analysis

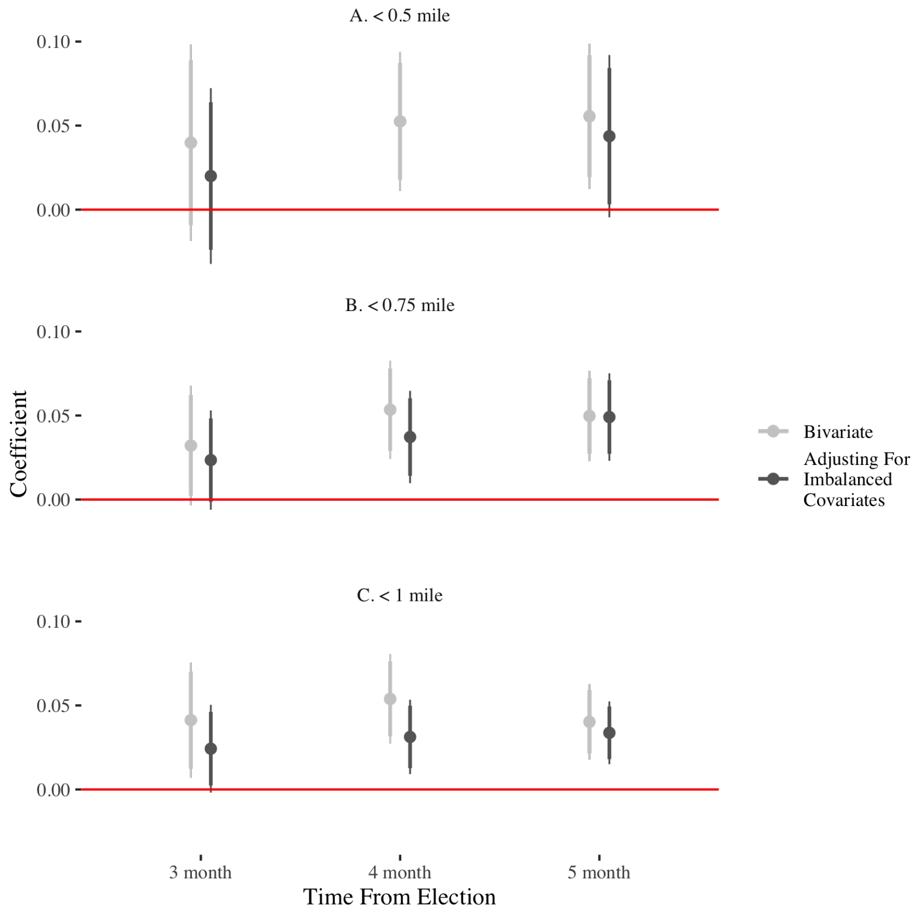

Figure D24: Coefficient Estimates for Timing of Exposure to Police Killing Among Precincts Close to Police Killings of Civilians (MPD-Served Precincts Only, Abstainers Included in % Measure J Denominator). Panels display different spatial thresholds for defining "exposure" and columns display different temporal bandwidths around the 2020 Election. Coefficient color denotes the exclusion/inclusion of control covariates. 95% CIs displayed derived form HC2 robust standard errors.

D.7.2 Abstention Rate Outcome in Design-Based Analysis

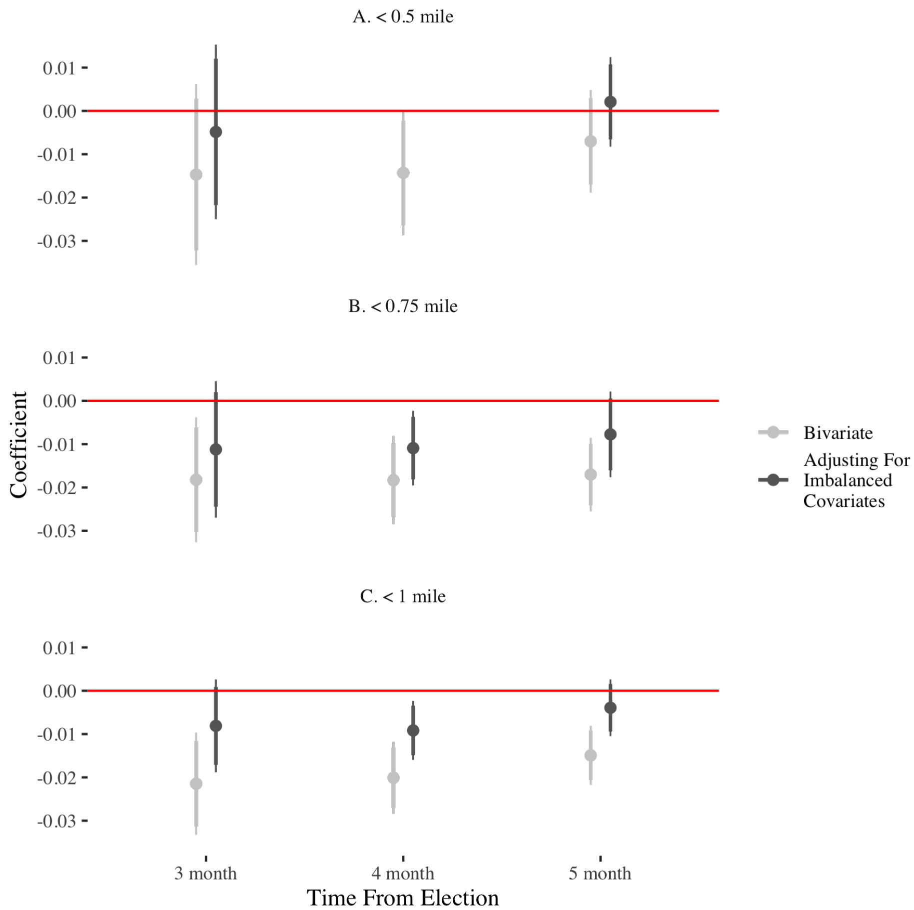

Figure D25: Coefficient Estimates for Timing of Exposure to Police Killing Among Precincts Close to Police Killings of Civilians (MPD-Served Precincts Only, Abstention Rate Outcome). Panels display different spatial thresholds for defining "exposure" and columns display different temporal bandwidths around the 2020 Election. Coefficient color denotes the exclusion/inclusion of control covariates. 95% CIs displayed derived form HC2 robust standard errors.