Political Responses to Hate Crimes*

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Abstract: We investigate how targeted groups respond politically to racially-targeted hate crimes that occur in their local communities. We combine incident-level administrative data on hate crimes in Los Angeles County from 2014 to 2022 with individual voter files, and leverage the hyperlocal variation in the geography and timing of these incidents. We show that serious anti-Hispanic hate crimes result in a 1.6 percentage points increase in voter turnout among nearby Hispanic voters compared to their White counterparts. This mobilization effect is mainly driven by communities with a high density of Hispanic population and the presence of Hispanic advocacy and community service organizations. We find no evidence of changes in the voter registration or migration patterns. Additionally, we demonstrate that hate crimes are associated with shifts in voters' policy preferences, particularly those relating to combating crime and affirmative action. However, we do not find significant changes in political participation among Black and American Asian communities following anti-Black and anti-Asian hate crimes, respectively. The substantial demographic presence and extensive network of community organizations within the Hispanic community in Los Angeles County may play a pivotal role in fostering the mobilization effect.

Keywords: hate crimes, minority, political participation, policy preference

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1 Introduction

Hate crimes persist as a significant concern globally, with 11,634 incidents recorded in the U.S. in 2022 alone (Dancygier and Green, 2010). Unlike typical criminal acts, hate crimes are unique because they stem from the perpetrator's intent to threaten specific communities, fostering fear and triggering broad societal consequences. These traumatic events could discourage civic participation and threaten the foundations of democracy. However, they may also spur collective action, motivating affected individuals to band together and assert their rights in response to these group threats (Fouka, 2019). Despite the crucial role of civic engagement in addressing these issues (Farrell and Lockwood, 2023), our comprehension of how communities politically react to local hate crimes remains limited.

The interplay between mobilization and intimidation effects underscores the complexity of community responses to hate crimes, emphasizing the need for empirical investigation into their implications for democratic participation. Nevertheless, disentangling these competing effects poses substantial data and methodological challenges. First, the FBI's Uniform Crime Reporting (UCR) Program, a widely used source of hate crime data, suffers from significant underreporting and lacks detailed location information, making it unsuitable for most rigorous research (Kaplan, 2021). Moreover, the occurrence of hate crimes often correlates with various socio-economic factors that can potentially impact political participation, including rates of non-bias-motivated crimes and economic conditions.

To address the challenges of data reliability and granularity, we leverage a unique incident-level administrative dataset on hate crimes in Los Angeles County from 2014 to 2022, compiled by the Los Angeles County Commission on Human Relations (LACCHR).[1] The LACCHR has been tracking hate crimes since 1980, drawing from diverse sources such as law enforcement agencies, educational institutions, community organizations, and direct reports from victims. Each reported incident undergoes rigorous independent review by LACCHR using consistent standards. Crucially for identification, this dataset provides precise geolocation data for each hate crime, enabling us to capture highly localized exposure to these incidents. To further mitigate concerns about under-reporting (Kena and Thompson, 2021), we focus our analysis on Part I offenses – serious crimes such as murder, aggravated assault, and robbery. The severity of these offenses not only makes them less likely to be underreported but also amplifies their

[1] https://hrc.lacounty.gov/

potential impact on community responses.

To tackle the identification challenges arising from the correlation between hate crimes and other socio-economic factors, we adopt an empirical strategy that leverages hyperlocal variations in the geography and timing of hate crimes. Our approach compares changes in political participation over time among voters residing very close to a hate crime incident (within 0.3 miles) with those living slightly further away (0.3 to 1.5 miles) but still within the same neighborhood. It allows us to control for broader socio-economic factors and trends that might affect political participation. This strategy is based on the fact that most hate crimes receive little media coverage and tend to spread within the local community through word of mouth. Furthermore, hate crimes typically target specific groups, allowing us to compare the political participation of voters from these targeted groups with that of White voters before and after the occurrence of hate crimes. These three sources of variation in exposure to hate crimes—location, timing, and targeted group—allow us to isolate the specific effects of hate crimes from broader reactions to local criminal activity or other confounding factors.

Our primary outcome of interest is voter turnout in general elections. We integrate the hate crime data with the individual-level L2 voter file, which contains snapshots of all registered voters in Los Angeles County from 2014 to 2024, enabling us to link hate crime exposure to individual voter turnout records. Our analysis indicates that anti-Hispanic hate crimes significantly increase voter turnout among nearby Hispanic voters. This mobilization effect demonstrates a notable spatial decay, being most potent for voters in close proximity and diminishing beyond a 0.3-mile radius. Furthermore, the event study plot shows that the effect is most pronounced in the general election immediately following the incident. Overall, anti-Hispanic hate crimes result in an average increase of 1.6 percentage points in Hispanic voter turnout in the surrounding areas – equivalent to a 17% reduction in the racial turnout gap. This electoral response reflects changes in political behavior rather than demographic shifts, as we find no evidence of selective migration or voter registration responses. We do not find significant spillover effects on non-targeted racial groups, suggesting that hate crimes generate highly specific political responses within victimized communities. Notably, we do not observe similar mobilization effects among Black and Asian American communities following hate crimes targeting their groups, suggesting that the political response to hate crimes may be context-dependent.

To understand the mechanisms driving these effects, we first examine whether individual-level characteristics explain the heterogeneous responses across racial groups. Using matched samples of Hispanic voters that mirror the socioeconomic and political profiles of Black and American Asian voters, we find that the mobilization effect persists, suggesting that contextual rather than individual factors drive the differential responses. We then explore three key contextual mechanisms: community density, institutional infrastructure, and media coverage. Our analysis shows that the mobilization effect is more pronounced in areas with high Hispanic population density and a strong presence of Hispanic advocacy organizations, with the most substantial effects occurring where both factors coexist. The limited media coverage of hate crimes in our sample suggests that local media plays a minimal role in driving these effects. Consistent with this interpretation, we find that anti-Black and anti-Asian hate crimes frequently occur in areas with lower concentrations of their respective populations. This may explain the absence of political mobilization effects among these groups, as weaker community networks could impede the dissemination of information.

The political response to hate crimes can manifest through multiple channels beyond voter turnout. First, we observe significant shifts in policy preferences reflected in voting patterns on state propositions. In the aftermath of hate crimes, affected areas exhibit increased opposition to criminal justice reform measures, particularly voting against propositions aimed at reducing penalties for certain offenses. Additionally, these communities show stronger support for affirmative action policies, indicating that hate crimes may raise awareness of systemic inequalities. These changes in policy preferences may also contribute to a higher turnout rate. Lastly, we observe broader political engagement through increased candidate entry: cities experiencing hate crimes witness a significant rise in Hispanic candidates running for municipal offices. Overall, the increase in descriptive representation suggests that hate crimes can act as a catalyst for broader political participation, underscoring how discriminatory violence prompts significant changes in political behavior and preferences within affected communities.

This paper makes two key contributions to the literature. First, it directly contributes to the growing body of research on hate actions. While existing research primarily focuses on the causes of hate sentiment and hate crimes, highlighting the significant roles of mass and social media (Müller and Schwarz, 2020, 2023; Ang, 2023; Jiménez Durán, Müller and Schwarz, 2023), immigration (Fouka and Tabellini, 2022; Couttenier et al., 2024; Zonszein and Grossman, n.d.), climate factors (Eberle, Rohner and Thoenig, 2020; Du, 2023), and, more recently, the impact

of COVID-19 (Cao, Lindo and Zhong, 2023; Dipoppa, Grossman and Zonszein, 2023), there is little evidence on how local communities respond to hate crimes. Given that hate crimes, as a form of "message crime," create significant externalities due to their targeted nature (Perry and Alvi, 2012; Stotzer and Sabagala, 2020; Jaskiewicz, 2023), understanding their consequences is crucial. We explore the significant political consequences of hate crimes within local communities and analyze the key drivers of community mobilization, namely group density and the role of local organizations. More broadly, our study examines how minority communities respond to public acts of discrimination and racism—an issue that is both far-reaching in scope and fundamental to deepening our understanding of race and inequality.

Second, this article adds to a burgeoning body of research illustrating the influence of violence on electoral participation. These strands of literature investigate how the presence of violence can shape an individual's involvement in the democratic process, including terrorist attacks (Berrebi, 2008; Gould and Klor, 2010; Montalvo, 2011; Hersh, 2013; Getmansky and Zeitzoff, 2014), mass and school shooting (Luca, Malhotra and Poliquin, 2020; Hassell, Holbein and Baldwin, 2020; Yousaf, 2021; Garcia-Montoya, Arjona and Lacombe, 2022; Marsh, 2023), police violence (Ang and Tebes, 2023; Morris and Shoub, 2024), and lynching (Jones, Troesken and Walsh, 2017; Williams, 2022). Mass and school shootings generally do not affect voter turnout rates at the county level but influence voters' policy preferences on gun control and increase Democratic Party vote shares (Hassell, Holbein and Baldwin, 2020; Yousaf, 2021; Garcia-Montoya, Arjona and Lacombe, 2022). Violence against minority groups, such as the historical lynching of Black individuals in the United States, has been found to discourage Black voter participation both in the short and long term (Jones, Troesken and Walsh, 2017; Williams, 2022). While police violence can lead to a 3%–5% increase in voter registration and vote counts, this effect is highly localized and is primarily observed within the census block where the violence occurred (Ang and Tebes, 2023). By examining hate crimes—a contemporary form of discriminatory violence—we provide insights into their mobilizing effect on minority voters. Contrary to the deterrent effects of historical acts such as lynching, hate crimes do not dissuade voter participation. In fact, their impact is more substantial in magnitude and broader in geographic scope compared to the effects of police violence.

2 Data

We focus our analysis on Los Angeles County, the most populous and one of the most ethnically diverse counties in the United States. According to the 2020 Census, Los Angeles County has over 10 million residents, with 48.0 percent identifying as Hispanic, 25.6 percent as White, 15.0 percent as Asian, and 7.9 percent as Black.[2] Our primary data sources are two administrative datasets: an incident-level dataset on hate crimes from the Los Angeles County Commission on Human Relations (LACCHR) and an individual-level voter file from L2, which includes the universe of registered voters in Los Angeles County and their turnout records. Additionally, we supplement our analysis with data on political outcomes from other sources, specifically block-level vote share data for propositions from the Statewide Database and candidate data for city offices from the California Elections Data Archive.

2.1 Data on Hate Crimes

Our hate crime data are provided by the Los Angeles County Commission on Human Relations (LACCHR).[3] Established in 1944 following the "Zoot Suit Riots," LACCHR is an official agency dedicated to resolving intercultural conflicts and eliminating bias and prejudice in Los Angeles County. As one of the oldest and largest organizations of its kind, LACCHR provides training to similar organizations on identifying and addressing hate crimes.

Monitoring and tracking hate crimes is one of LACCHR's flagship initiatives. Since 1980, the commission has compiled data from over 100 law enforcement agencies, educational institutions, community-based organizations, and direct reports from victims through 211 LA.[4] Each reported hate crime undergoes a thorough review by LACCHR to ensure consistency and accuracy in reporting.[5]

Under California Penal Code Section 422.55, a hate crime is defined as a criminal act committed, in whole or in part, because of one or more actual or perceived characteristics of the victim, including disability, gender, nationality, race or ethnicity, religion, and sexual

[2] Source: https://data.census.gov

[3] https://hrc.lacounty.gov/

[4] https://211la.org/

[5] Other LACCHR initiatives include the annual Hate Crime Report, Quarterly Network Against Hate Crime Meetings, the LA vs Hate Anti-Hate Initiative, and the LA County Anti-Racism, Diversity, and Inclusion Initiative.

orientation. In simpler terms, a hate crime is a criminal act motivated by bias or prejudice.[6]

An illustrative example from the *LACCHR 2018 Hate Crime Report* is as follows:

> *On August 27, 2021, in Long Beach, CA, a Latino male was exiting his apartment building when he nearly collided with a White male. The victim said, "Watch out, buddy." The suspect immediately responded, "Watch out for what, you f—— Mexican?" He then spat on the victim and repeatedly punched him, knocking him to the ground. As the victim tried to get up, the suspect kicked him and continued yelling racial slurs.*

Our dataset includes all hate crimes reported to LACCHR from 2014 to 2022, totaling approximately 5,500 incidents. This incident-level data provide detailed information on dates, exact locations, bias motivations, offense types, and the demographic profiles of both victims and suspects.[7] Panel A of Figure A1 presents the time trend for all hate crimes documented in Los Angeles County. There has been an increasing trend in hate crimes, mirroring the rising trend observed at the national level. Of these incidents, 45.5 percent targeted Black, Latino, or Asian individuals, with 19.6 percent classified as Part I crimes—serious offenses including murder (2.5 percent), robbery (8.1 percent), and aggravated assault (86.5 percent). We focus primarily on Part I hate crimes in our analysis due to their severity and lower likelihood of underreporting. Panel B of Figure A1 shows the time trend for all Part I hate crimes targeting Black, Latino, and Asian populations in Los Angeles County over the same period, following a similar pattern to that of all hate crimes.

Within these hate crimes, the Black community is the most targeted group, accounting for 62.3 percent of incidents. Anti-Latino biases are involved in 32.3 percent of cases, while 6.5 percent target the Asian American community, with the majority occurring after the onset of COVID-19. Among suspects involved in anti-Black hate crimes, 61.2 percent are Hispanic, and similarly, 57.2 percent of suspects in anti-Latino hate crimes are Black. White individuals

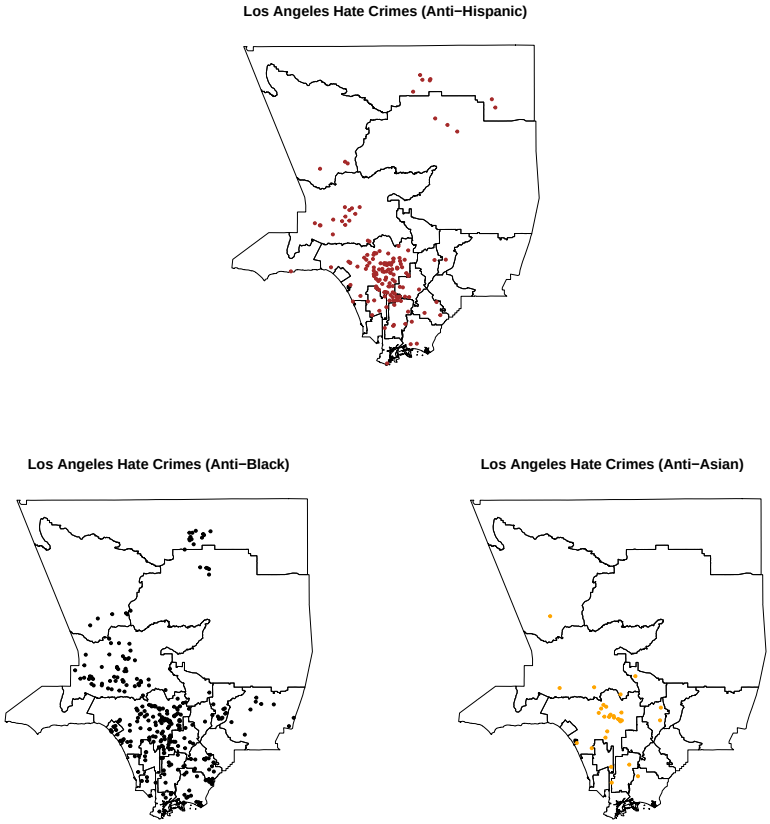
[6] A closely related concept is hate speech, which is pervasive on social media and is frequently sanctioned (Jiménez Durán, 2021). However, hate speech is often not classified as a hate crime. Derogatory words or slurs directed at a member of a protected class, without an accompanying threat of violence, are considered hate incidents, not crimes. Additionally, graffiti is classified as a hate crime only when it involves vandalism specifically targeting and disparaging a group protected under hate crime laws.

[7] We manually geocoded each address into longitude and latitude coordinates using Google Maps. Due to privacy concerns, the exact locations are obfuscated by rounding the last two digits of the street number to "50." Assuming each unit represents a distance of 0.008 miles, this process introduces an average measurement error of approximately 0.1 miles in the exact location of the hate crime.

account for 28.8 percent of suspects involved in anti-Black hate crimes and 24.5 percent of suspects involved in anti-Latino hate crimes.

Figure 1 illustrates the spatial distribution of hate crimes targeting Black, Hispanic, and Asian communities. Hate crimes occur across the entirety of Los Angeles County rather than being concentrated in specific neighborhoods, although certain areas experience higher incidences than others. This spatial variation, which may correlate with area-specific characteristics, motivates our identification strategy that leverages hyperlocal variations in the location and timing of hate crimes.

Figure 1: Map of Hate Crimes in L.A.



Notes: This figure shows the spatial distribution of hate crimes from 2014 to 2022. The dots in each panel represent Part I hate crimes against Black, Hispanic, and Asian individuals, with colors corresponding to each group.

2.2 Data on Voter Turnout

We utilize a comprehensive dataset from the California Historical Voter File (2014–2024), provided by the nonpartisan voter data vendor L2.[8] This dataset offers snapshots of all registered voters in Los Angeles County (and California) from 2014 to 2024, updated approximately four times per year.[9] Crucially, it provides precise residential addresses for each voter, allowing us to accurately measure proximity to hate crime incidents by matching each hate crime's location to the voter's address in the corresponding year. The L2 Voter File includes each voter's complete turnout history for all general elections from 2008 to 2022, enabling us to track individual political participation over an extended period. Additionally, it contains detailed demographic information about voters, such as gender, age, and predicted ethnicity.[10]

As of 2020, there were approximately 4.8 million registered voters in Los Angeles County. Among them, 43.8 percent are identified as Hispanic, 37.4 percent as White, 11.2 percent as Asian, and 7.7 percent as Black. A significant turnout gap exists among these demographic groups. In the 2020 presidential election, the turnout rates for Hispanic, White, Asian, and Black registered voters were 71.1 percent, 80.3 percent, 75.1 percent, and 69.1 percent, respectively. In addition to voter turnout, we use the L2 Voter File to analyze migration patterns and gain insights into voter registration trends.

2.3 Data on Policy Preference

To examine the impact of hate crimes on policy preferences, we utilize election data on three significant California propositions that addressed criminal offenses or affirmative action.

The first, Proposition 47 in 2014—known as the "Safe Neighborhoods and Schools Act"—reclassified certain nonviolent felonies as misdemeanors, specifically targeting drug possession and theft crimes under $950. This proposition aimed to reduce prison populations and redirect savings to crime prevention and support programs. It passed with a 59.6 percent vote share.

[8] https://l2-data.com/

[9] For each year, we use the voter file updated either in the first or second quarter, depending on data availability.

[10] California does not mandate voters to self-report their race and ethnicity. Therefore, L2 employs a sophisticated algorithm utilizing full names, census block data, and known marriage indicators to predict race and ethnicity. We also implement two additional approaches to predict race and ethnicity—Bayesian Improved Surname Geocoding (Imai and Khanna, 2016) and fully Bayesian Improved Surname Geocoding (Imai, Olivella and Rosenman, 2022)—and our main findings remain consistent.

The second, Proposition 57 in 2016—titled the "Public Safety and Rehabilitation Act"—made nonviolent felons eligible for parole consideration once they completed the full term for their primary offense. It authorized sentence credits for rehabilitation, good behavior, and education, and allowed judges, rather than prosecutors, to decide whether to try certain juveniles as adults. It passed with a 64.5 percent vote share.

The third, Proposition 16 in 2020, sought to repeal Proposition 209 (passed in 1996), which prohibited state governmental institutions from considering race, sex, color, ethnicity, or national origin in public employment, education, and contracting. Proposition 16 aimed to reinstate affirmative action in California's public sector. The measure was defeated, with 57 percent voting against and 43 percent in favor.

We obtain block-level estimates of the share of ballots cast for and against each proposition from the California Statewide Database, providing granular data for analyzing voting patterns across different communities.[11]

2.4 Data on Candidate Entry

Data on candidates running for city elections in Los Angeles County are sourced from the California Elections Data Archive (CEDA).[12] CEDA contains detailed information on local elections in California, including election dates, offices, candidate names, occupations, incumbent status, and vote shares. Our focus is on city council elections in Los Angeles County from 2004 to 2022. The dataset encompasses 90 cities and includes over 5,000 candidates who ran for city office during the sample period, with approximately 1,900 elected. Since there is no available information on the candidates' race or ethnicity, we predict race and ethnicity based on full names using the R package *rethnicity*.[13]

3 Empirical Strategy

There is limited causal evidence regarding the impact of hate crimes on local communities. This is because analyzing the correlation between hate crimes and neighborhood out-

[11] https://statewidedatabase.org/

[12] https://scholars.csus.edu/

[13] Beach and Jones (2017) and Beach et al. (2024) construct a dataset identifying the race and ethnicity of candidates who ran for city council in CEDA. However, their dataset covers only the period between 2005 and 2011 and includes candidates who narrowly won or lost the election, making it particularly suited for close-election research designs.

comes is confounded by the fact that hate crimes tend to happen more frequently in disadvantaged areas with high rates of homicide and poverty. Additionally, the political participation of minority groups may, in itself, result in a rise in hate crimes (Zonszein and Grossman, n.d.). Therefore, if we regress local hate crime on voter turnout, it would likely be biased by geographic variations in political preferences and engagement.

To address this, we exploit hyperlocal variation in exposure to hate crimes within neighborhoods similar to Ang (2021). In essence, identifying variation comes from comparing changes in political participation over time among voters residing very close to a hate crime with those living slightly further away but still in the same neighborhood. Therefore, both groups are likely to have similar backgrounds and experience comparable local conditions, except for the occurrence of the hate crime itself. This comparison is based on the fact that most of the sampled hate crimes received little to no media coverage, resulting in any effects being highly localized and geographically concentrated. Furthermore, since hate crimes primarily target minority groups, we can compare minority voters with white voters to control for responses to crimes, as well as trends in political participation within the local area. By combining these three comparisons, we employ a triple differences stacked event study approach to estimate the causal impact of hate crimes on voter behavior within local communities.

To ensure we capture the most salient and reliably reported incidents, we focus our analysis on Part I offenses, including aggravated assault, robbery, murder, burglary, and arson. This approach not only concentrates on the most salient events but also mitigates potential concerns about underreporting, which should be less prevalent for these serious offenses. Our final analysis encompasses 155 hate crime events targeting Hispanic individuals, 299 targeting Black individuals, and 31 targeting Asian individuals.

For each hate crime, our sample includes voters from the targeted group as well as white voters residing within a 1.5-mile radius of the incident, and we observe their turnout in the three general elections before and the three general elections after the hate crime.[14] For individuals who experienced multiple separate incidents (i.e., hate crimes occurring nearby on different days) during the sample period, we consider only the first incident.

[14]Most state and local elections in California are on-cycle elections.

3.1 Graphical Evidence

In our empirical strategy, we begin by presenting graphical evidence to illustrate the spatial dynamics of hate crimes' impact on political participation. Our approach is predicated on the hypothesis that the effects of hate crimes on voter turnout dissipate with increasing distance from the incident location. To rigorously examine this spatial heterogeneity, we employ a stacked difference-in-difference-in-differences (DDD) specification, which allows us to estimate the differential effects of hate crimes on targeted groups across various distance bands.

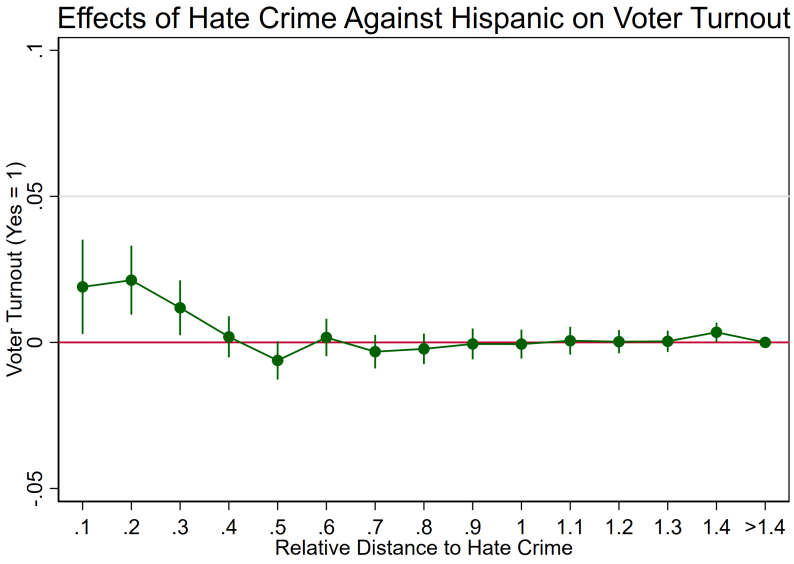
$$\begin{aligned} Y_{it} = {} & \alpha \cdot \text{Post}_t + \theta \cdot \text{Targeted}_i + \sum_d \gamma_d \cdot \text{Dist}_{i(d)} + \delta \cdot \text{Post}_t \cdot \text{Targeted}_i \\ & + \sum_d \xi_d \cdot \text{Targeted}_i \cdot \text{Dist}_{i(d)} + \sum_d \eta_d \cdot \text{Post}_t \cdot \text{Dist}_{i(d)} \\ & + \boxed{\sum_d \beta_d \cdot \text{Post}_t \cdot \text{Targeted}_i \cdot \text{Dist}_{i(d)}} + \varphi_i + \zeta_{ct} + \epsilon_{it} \end{aligned} \tag{1}$$

where Y_{it} is a dummy variable that indicates whether voter i participated in the general election in year t. $Targeted_i$ indicates whether the voter belongs to the group targeted by the hate crime, $Post_t$ indicates whether the election in year t occurs after the hate crime, and $\sum_d \text{Dist}i(d)$ represents a set of mutually exclusive treatment indicators that track a voter's distance to the hate crime. For voters who were exposed to multiple hate crimes during the sample period, we define treatment based on their earliest exposure to a nearby hate crime to avoid contamination from subsequent incidents.[15] Of particular interest is the triple interaction term, $\sum d\beta_d \cdot \text{Post}t \cdot \text{Targeted}i \cdot \text{Dist}i(d)$, which captures the differential effect of hate crimes on the targeted group's turnout across different distance bands, relative to non-targeted groups and pre-hate crime periods. This specification allows us to trace out the spatial decay of hate crimes' impact with precision. The comprehensive regression equation incorporates a robust set of fixed effects, including voter fixed effects φ_i and census tract-election fixed effects ζct. Standard errors are clustered at census tract level.[16]

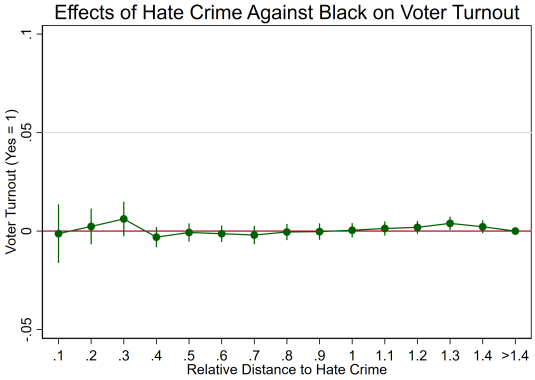
We estimate this model separately for anti-Hispanic, anti-Black, and anti-Asian hate crimes, producing a series of graphical representations that plot the estimated coefficients β_d

[15] In robustness analysis, we also drop students exposed to multiple killings and find similar results.

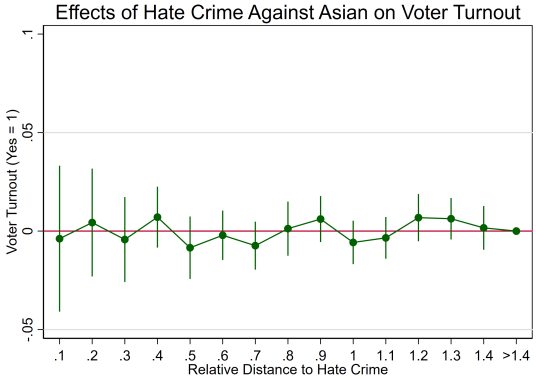
[16] In the 2010 Census, there are 2,344 census tracts in Los Angeles County. Each census tract is ideally designed to contain about 4,000 people and 1,600 housing units. On average, a census tract covers an area of approximately 1.7 square miles in Los Angeles County.



Panel A: Hate Crimes Against Hispanic



Panel B: Hate Crimes Against Black



Panel C: Hate Crimes Against Asian

Figure 2: Effects on Voter Turnout by Distance

Notes: This figure reports stacked triple-differences estimates of the effects of hate crime based on equation (1). We incorporate voter fixed effects and census tract-year fixed effects. Panel A displays the effect of distance from hate crimes against Hispanic individuals on voter turnout, while Panels B and C demonstrate the impact of hate crimes targeting Black and Asian voters. The standard errors are clustered at census tract level.

against distance in Figure 2. These figures reveal nuanced patterns in the spatial reach of hate crimes across different targeted groups. For Hispanic voters, we observe significant mobilization effects among those residing nearby, which diminish with distance and disappear beyond 0.3 miles from the hate crime location, suggesting a relatively localized impact. In contrast, no

significant effects are observed across varying distances for Black andAsian American voters.

These findings illustrate spatial dynamics of hate crimes in local communities and further guide us to define treated distance in the subsequent empirical analysis. Based on these results, we refine our definition of nearby areas to be within 0.3 miles based on these results. This data-driven approach to defining treatment proximity enhances the precision of our estimates and allows us to capture the most relevant spatial scale of hate crimes' effects for each targeted group.

To further validate our empirical approach, we compare the demographic composition of voters residing near hate crime locations with those living slightly farther away across multiple distance thresholds. Table 1 demonstrates remarkable consistency in key demographic characteristics regardless of the chosen boundary. When comparing populations within and beyond 0.3 miles (columns 2-3), we observe only minor differences in the Hispanic population (44.0% vs. 44.3%) and Black population (13.7% vs. 13.0%). This pattern of demographic balance persists when examining alternative thresholds at 0.4 miles (columns 4-5) and 0.5 miles (columns 6-7), with virtually identical population shares across racial groups. The most notable variation appears in the gender composition, with a slightly higher male population in the immediate vicinity of hate crimes (48.8% within 0.3 miles compared to 47.1% beyond). However, this small difference gradually diminishes when examining wider radius boundaries. Other socio-demographic characteristics, including the White population (consistently around 33%), average age (ranging from 45-47 years), and Democratic party affiliation (approximately 59-60%), exhibit minimal variation across all distance thresholds. The stability of these demographic patterns across multiple spatial boundaries provides strong support for our identification strategy, suggesting that our results are unlikely to be driven by systematic differences in neighborhood composition.

Table 1: Summary Statistics

	(1) Full	(2) ≤0.3 mi.	(3) > 0.3 mi.	(4) ≤0.4 mi.	(5) > 0.4 mi.	(6) ≤0.5 mi.	(7) > 0.5 mi.
White Frac.	0.329	0.329	0.330	0.329	0.330	0.328	0.330
Hispanic Frac.	0.443	0.440	0.443	0.442	0.443	0.442	0.443
Black Frac.	0.130	0.137	0.130	0.132	0.130	0.130	0.130
Asian Frac.	0.097	0.096	0.097	0.097	0.097	0.097	0.099
Male Frac.	0.472	0.488	0.471	0.485	0.471	0.481	0.471
Age	46.4	45.7	46.5	45.8	46.5	46.0	46.5
Democratic Frac.	0.597	0.593	0.597	0.594	0.597	0.593	0.597
Observations	16,776,196	819,715	15,956,481	1,435,291	15,340,905	2,205,382	14,570,814

Notes: This table presents summary statistics using L2 voter file data. For each hate crime incident, we retain voters residing within 1.5 miles of the crime location in the year of occurrence. We then merge each voter's turnout history for the election year, creating a panel dataset. This process is repeated for each hate crime, and the samples are pooled together. Column (1) shows descriptive statistics for the full sample. Columns (2) and (3) show subsample statistics based on a 0.3-mile distance from the hate crime location. Columns (4) and (5) display subsample statistics based on a 0.4-mile distance from the hate crime location. Columns (6) and (7) present subsample statistics divided by a 0.3-mile distance from the hate crime location.

3.2 Estimating Specification

Building upon our graphical evidence, we proceed to our main event study analysis. Our empirical strategy leverages the spatial and temporal variation in hate crime occurrences, allowing us to isolate the impact on targeted groups while controlling for various confounding factors. We estimate the following base equation on the voter panel data:

$$\begin{aligned} Y_{it} = &\sum_{j\neq -1} \alpha_j \cdot \text{Election}_j + \theta \cdot \text{Targeted}_i + \gamma \cdot \text{Nearby}_i + \delta \cdot \text{Targeted}_i \cdot \text{Nearby}_i \\ &+ \sum_{j\neq -1} \xi_j \cdot \text{Election}_j \cdot \text{Targeted}_i + \sum_{j\neq -1} \eta_j \cdot \text{Election}_j \cdot \text{Nearby}_i \\ &+ \boxed{\sum_{j\neq -1} \beta_j \cdot \text{Election}_j \cdot \text{Targeted}_i \cdot \text{Nearby}_i} + \varphi_i + \zeta_{ct} + \epsilon_{it} \end{aligned} \tag{2}$$

where Y_{it} is a dummy variable that indicates whether voter i participated in the general election in year t. $Nearby_i$ denotes whether a voter resides within 0.3 miles of a hate crime, representing the treated distance. $\sum_{j\neq -1} Election_j$ represents a set of general elections occurring around the time of hate crimes (spanning three elections before and three elections

after), where the variable is set to 1 if the election in year t is j elections away from the occurrence of a hate crime. The key parameter of interest is β_j, which captures the change in voter turnout in general elections before and after a hate crime for the targeted group living within the nearby area (0.3 miles) compared to those residing slightly farther away (0.3 to 1.5 miles), relative to the same spatial comparison for white voters.

We, again, include a comprehensive set of fixed effects and controls in the specification to address potential confounding factors. Voter fixed effects φ_i control for individual characteristics that do not change over time, while census tract-election fixed effects λ_{ct} account for local factors that vary over time. Standard errors are clustered at the census tract level.

In implementation of the stacked regression approach, we assign equal weights to each hate crime event. This method allows us to aggregate the effects across multiple incidents while preserving the integrity of our event study design. By stacking the data around each hate crime occurrence, we also address the issue of "forbidden comparison" in heterogeneous treatment effects, ensuring that treated units are compared only with the never-treated group over time (Goodman-Bacon, 2021).

4 Baseline Results

4.1 Voter Turnout

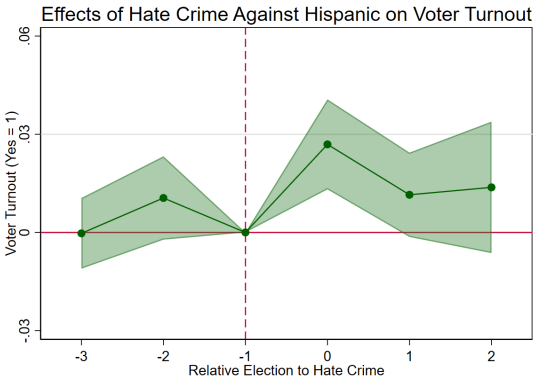
Figure 3 presents the baseline results from our stacked triple-differences event study, illustrating the heterogeneous effects of hate crimes on voter turnout across different targeted groups. The figure comprises three panels, each depicting the impact on Hispanic, Black, and Asian American voters respectively.

Panel A, which focuses on hate crimes against Hispanic individuals, reveals a notable mobilization effect. Following the occurrence of a hate crime, we observe a significant increase in voter turnout among Hispanic voters living close to the incident location. This mobilization effect is largest in the election immediately following the hate crime (period 0), with point estimates suggesting an increase in turnout of approximately 3 percentage point. The mobilization effect decreases over time but remains positive and economically significant.

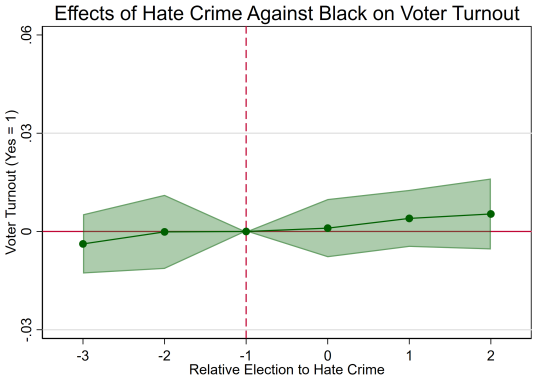
Panels B and C depict the effects of hate crimes against Black and Asian individuals, respectively. For Black voters (Panel B), we observe no statistically significant change in turnout

following hate crimes. The point estimates remain near zero across all post-treatment periods, with confidence intervals consistently containing the zero. This lack of response suggests that anti-Black hate crimes do not significantly mobilize the Black community, despite the fact that Black individuals remain the most frequent targets of hate crimes. Similarly, Panel C shows that hate crimes against Asian individuals do not lead to significant changes in voter turnout among Asian Americans. It is important to note that our analysis includes only 31 anti-Asian hate crimes, most of which occurred after 2020. The limited number of observations explains the wide confidence interval for the third election following the hate crimes. Importantly, all three panels exhibit parallel trends, with point estimates near zero and statistically insignificant in the periods leading up to the hate crime.

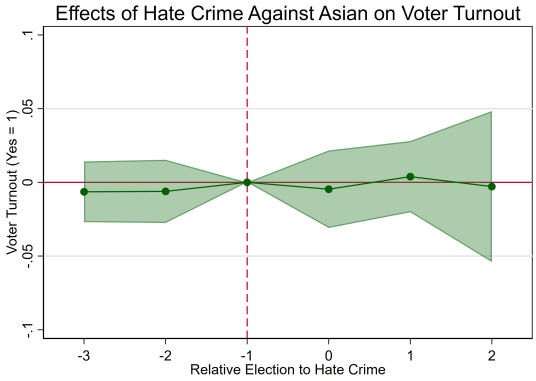
Overall, these results present a nuanced picture of how different communities respond politically to targeted violence. The mobilization effect observed among Hispanic voters contrasts with the null findings for Black and Asian American voters, suggesting that the political impact of hate crimes may vary significantly across minority groups.



Panel A: Hate Crimes Against Hispanic



Panel B: Hate Crimes Against Black



Panel C: Hate Crimes Against Asian

Figure 3: Stacked Triple Differences Event Studies: Baseline Results

Notes: This figure presents stacked triple-differences estimates and 90% confidence intervals for the effects of hate crimes based on equation (2). Panel A shows the impact of hate crimes against Hispanics, while Panels B and C show the impact on Black and Asian American voters separately. The standard errors are clustered at census tract level in all regressions.

To summarize the results, we modified Equation (2) by combining the first three year dummies following each hate crime into a single post dummy. Table 2 presents our baseline results and various robustness checks for the impact of hate crimes on voter turnout across different ethnic groups. The baseline estimate in column (1) shows that hate crimes against Hispanics lead to a 1.6 percentage point increase in voter turnout among Hispanic voters, which is equivalent to 3% of the mean and 17.0% of the racial turnout gap.

This effect remains stable and significant across various robustness checks. First, we include hate crime event fixed effects in column 2, which helps control for the heterogeneity of

hate crimes in terms of their characteristics and context. Second, we construct data on census block-level crimes using incident-level Part I crime data from Los Angeles County and add this variable as a control in column 3.[17] This helps account for the impact of general crime on political responses. Third, we use an alternative neighborhood definition—zip code—and incorporate zip code-election fixed effects in column 4. There are 290 zip code areas in Los Angeles, compared to 2,344 census tracts. Fourth, in column 5, we exclude voters who have been exposed to multiple hate crimes during our sample period to ensure our results are not driven by repeated exposure to discriminatory violence. Finally, to isolate changes in the electorate, we exclude movers in column 6 and newly registered voters in column 7. The consistency of these results across different specifications provides further credibility to our main findings, indicating a robust mobilization effect among Hispanic voters in response to hate crimes. Panels B and C present the results for Black and Asian American voters, respectively. Once again, we find that hate crimes do not significantly impact voting behavior in these communities: the magnitude is economically small and not statistically significant.

[17]Data source: https://lasd.org/transparency/part1and2crimedata/

Table 2: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Turnout (=1)						
	Base	Alt. Controls				Alt. sample	
Panel A: Hispanic *Average Turnout Rate : 0.509*							
Average Treatment Effects	0.016***	0.017***	0.020***	0.016**	0.014***	0.017***	0.016***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Obs.	17,494,480	17,494,480	17,494,817	17,494,480	15,817,686	17,218,384	16,984,379
Panel B: Black *Average Turnout Rate: 0.530*							
Average Treatment Effects	0.004	0.005	0.004	-0.003	0.005	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
Obs.	17,478,552	17,478,552	17,478,552	17,478,987	15,918,939	17,017,541	17,065,937
Panel C: Asian American *Average Turnout Rate: 0.530*							
Average Treatment Effects	0.001	0.001	0.001	0.001	0.007	0.001	-0.000
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Obs.	2,621,583	2,621,583	2,621,583	2,621,583	2,478,792	2,553,006	2,523,499
Voter Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Census tract-Election Fixed Effects	✓	✓	✓		✓	✓	✓
Crime Event Fixed Effects		✓					
Part I Crime			✓				
Zip code-Election Fixed Effects				✓			
Exclude					Multi-T	Movers	Regis.

Notes: The table presents the results of estimating equation (1) by replacing relative year indicators with a single post-treatment indicator. Treated distance refers to voters living within 0.30 miles of a hate crime in the given year, while the control group consists of voters residing 0.3-1.5 miles away. The control group comprises White voters, and the treated groups are Hispanic (Panel A), Black (Panel B), and Asian American Voters (Panel C). We conduct a triple-difference regression analysis, controlling for all relevant interaction terms across columns. We cluster standard errors at census tract level in all columns. Column (1) presents our baseline results, controlling for individual voter fixed effects, and census tract-election year FE. Column (2) adds hate crime event controls. Column (3) controls for Part I crime occurrence in the census block that year (affecting 9.7% of the sample). Column (4) replaces census tract-election year FE with Zip code-election year FE. The sample size is different due to missing census tract information for some voters. Column (5) excludes voters who have been treated multiple times. Column (6) excludes movers who relocated after the hate crime. Column (7) excludes new registrants who registered after the hate crime.

4.2 Migration Responses and Voter Registration

Beyond examining voter turnout responses, understanding how hate crimes affect community composition through migration and voter registration is crucial for interpreting our main results. To do so, we conduct two complementary analyses. First, we examine the impact of hate crimes on residential mobility patterns based on L2 voter file. Second, we analyze potential changes in the number of registered voters and first-time voter registrations following hate crime incidents.

4.2.1 Migration Responses

For each hate crime that occurred in year h, we create two snapshots of voters residing within a 1.5-mile radius of the incident. The first snapshot is taken in year $h-3$, and the second in year h. We then track whether these voters migrate out of the neighborhood, defined by census tract, over the next two years, specifically in years $h+1$ and $h+2$. The first snapshot, taken in year $h-3$, captures pre-hate-crime migration patterns, while the second snapshot, taken in year h, allows us to observe migration following the incident. We then estimate the following specification:

$$\begin{aligned} Migrate_{it} = \alpha \cdot \text{Targeted}_i + \beta \cdot \text{Nearby}_i + \delta \cdot \text{Post}_t \cdot \text{Targeted}_i \\ + \xi \cdot \text{Nearby}_i \cdot \text{Targeted}_i + \eta \cdot \text{Post}_t \cdot \text{Nearby}_i \\ + \boxed{\theta \cdot \text{Post}_t \cdot \text{Nearby}_i \cdot \text{Targeted}_i} + \lambda_{ct} + \epsilon_{it} \end{aligned} \tag{3}$$

where $Migrate_{it}$ indicates whether voter i migrated out of the neighborhood (defined at the census tract level) in the two years following t. Nearby_i is a dummy variable that equals 1 if the voter resides in the nearby region, defined as within 0.3 miles of a hate crime. Post_t is a dummy variable indicating whether the voter is observed in the second snapshot, created in the year of the hate crime t. Targeted_i equals 1 if the voter i belongs to the targeted group, and 0 if they are White. We control for census tract-year fixed effects λ_{ct}. Standard errors are clustered at the census tract level.

Table 3: Migration Responses to Hate Crime

VARIABLES	(1)	(2) Migration(=1)	(3)
Sample	Hispanic	Black	Asian
Nearby*Post*Targeted Group	-0.0135	-0.0221	0.00682
	(0.00994)	(0.0269)	(0.0126)
R-squared	0.062	0.071	0.076
Census-Tract-Year FEs	✓	✓	✓

Notes: This table shows the stacked triple-differences estimates using the Hispanic (Column 1), Black (Column 2), and Asian (Column 3) sample, respectively. Migration is defined as a voter moving out of the census tract area. Nearby refers to voters residing within 0.5 (0.3) miles of a hate crime occurrence in the given year, with the corresponding control being voters 0.5(0.3)-2 miles away. The control group comprises White voters, and the treated groups are Hispanic (Column 1), Black (Column 2), and Asian Voters (Column 3). We incorporate census tract-election fixed effects and cluster standard errors at census tract level in all regressions.

Table 3 presents the results of our migration analysis, examining whether hate crimes induce differential migration responses among targeted groups compared to non-targeted residents in the vicinity of these incidents. The results reveal no statistically significant effects on migration for any of the three targeted groups - Hispanic, Black, or Asian American residents. For Hispanic residents, we observe a small negative coefficient (-0.014), suggesting a slight, albeit insignificant, decrease in the probability of moving following a hate crime. Conversely, for Black and Asian residents, the coefficients are positive but extremely small (-0.022 and 0.007 respectively) and statistically indistinguishable from zero. These findings indicate that hate crimes do not substantially alter residential choices of targeted groups in the short to medium term. A caveat of our analysis of migration responses using L2 voter files is that these files only include registered voters. As a result, citizens who have never registered or non-citizens are not captured in the analysis. Additionally, L2 voter files do not track voters who migrate across states, meaning we cannot fully distinguish between out-of-state migration and voter deregistration. In the next section, we will directly examine if hate crimes affect voter registration at the census block level.

4.2.2 Voter Registration

Voter registration is the first step in participating in an election, and hate crimes may potentially motivate some citizens to register while discouraging some already registered voters from participating. Since the L2 voter file includes only registered voters, rather than the entire electorate, we are limited in our ability to conduct analysis at the individual level. Instead, we will examine voter registration trends in the smallest available geographic unit: the census block, and employ the following specification:

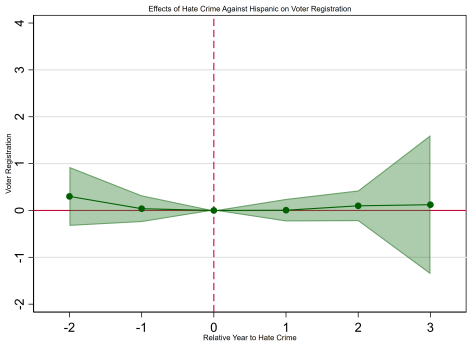
$$
\begin{aligned}
Y_{bgt} = & \sum_{j \neq -1} \alpha_j \cdot \text{Year}_j + \theta \cdot \text{Targeted}_g + \gamma \cdot \text{Nearby}_b + \delta \cdot \text{Targeted}_g \cdot \text{Nearby}_i \\
& + \sum_{j \neq -1} \xi_j \cdot \text{Year}_j \cdot \text{Targeted}_g + \sum_{j \neq -1} \eta_j \cdot \text{Year}_j \cdot \text{Nearby}_b \\
& + \boxed{\sum_{j \neq -1} \beta_j \cdot \text{Year}_j \cdot \text{Targeted}_i \cdot \text{Nearby}_b} + \varphi_b + \zeta_{ct} + \epsilon_{bgt}
\end{aligned} \tag{4}
$$

where Y_{bgt} represents the number of registered voters from ethnic group g in census block b in year t. $Targeted_g$ indicates whether the ethnic group g is the group targeted by the hate crime. $\sum_{j \neq -1} Year_j$ represents a set of years surrounding the occurrence of hate crimes (spanning three years before and three years after). The variable is set to 1 if year t is j years away from the hate crime incident. $Nearby_i$ denotes whether the distance from the geometric center of a census block to the location of the hate crime is less than 0.3 miles, representing the treated distance. Of particular interest is the triple interaction term, $\sum_{j \neq -1} \beta_j \cdot \text{Year}_j \cdot \text{Targeted}_i \cdot \text{Nearby}_b$, which captures the impact of hate crimes on voter registration before and after the hate crime. We control for census block fixed effects φ_b and census tract-year fixed effects ζ_{ct}. Standard errors are clustered at census tract level.

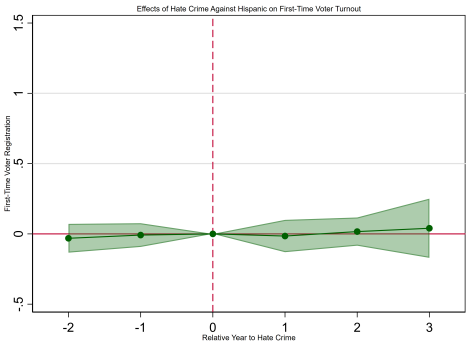
For each hate crime, our sample includes census blocks within a 1.5-mile radius of the incident. We focus on voter registration for the target group and white voters within an six-year time window, spanning three periods before and periods years after the hate crime.

Results are presented in Figure 4. We do not find that hate crimes significantly impact voter registration across all ethnic groups. We then focus on first-time voters, defined as individuals under 23 years old. This group exhibits different policy preferences but tends to have

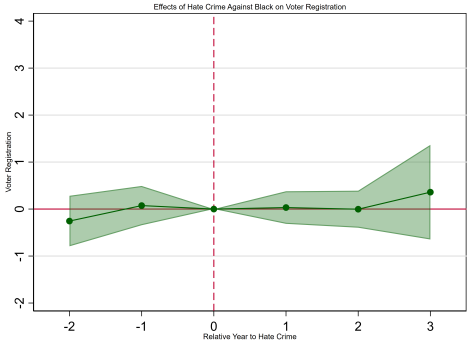
a low rate of political participation in elections. Once again, we do not find strong evidence that hate crimes significantly affect first-time voter registration across all ethnic groups.



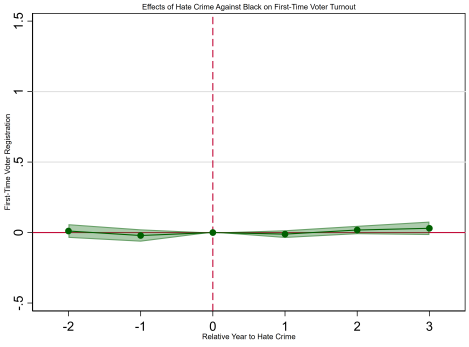
Panel A: Hispanic, All Voter



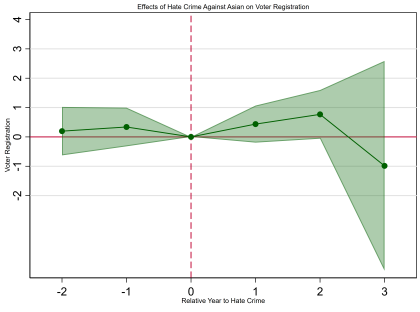
Panel B: Hispanic, First-time Voter



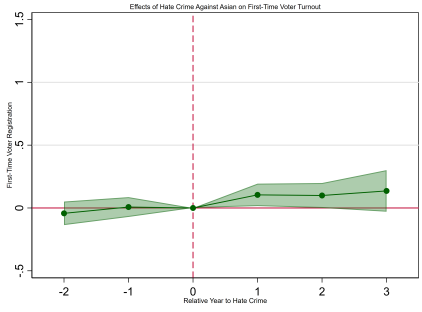
Panel C: Black, All Voter



Panel D: Black, First-time Voter



Panel E: Asian, All Voter

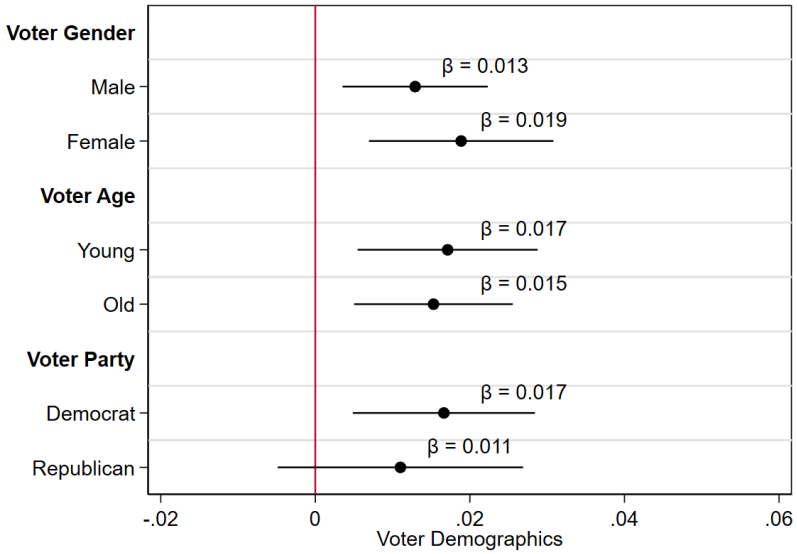


Panel F: Asian, First-time Voter

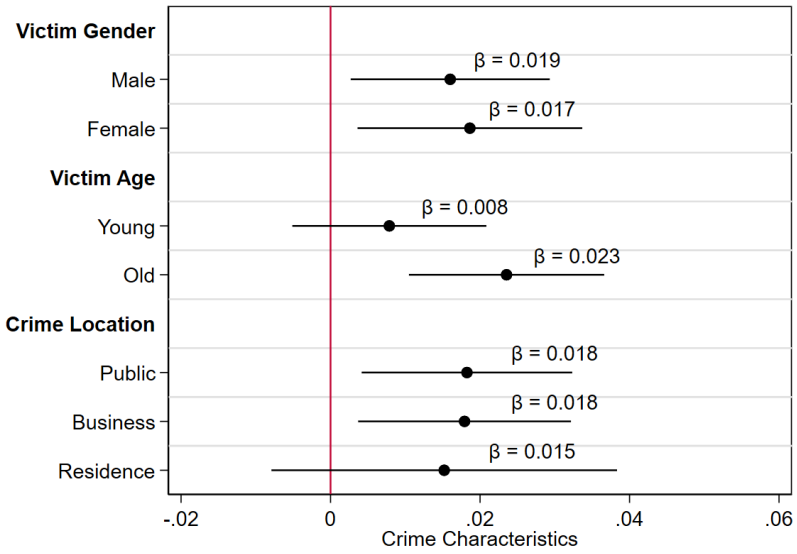
Figure 4: Effects of Hate Crimes on Voter Registration

Notes: This figure illustrates the impact of hate crimes on voter registration. All regressions include census block fixed effects and census tract-year fixed effects. Panels A and B analyze the impact of anti-Hispanic hate crimes on Hispanic voter registration, including both overall and first-time registrations. Panels C and D investigate the effects of anti-Black hate crimes, while Panels E and F study the impacts of anti-Asian hate crimes on voter registration. Standard errors are clustered at the census tract level.

4.3 Heterogeneous Analysis



Panel A: Heterogeneous Effects by Voter Demographics



Panel B: Heterogeneous Effects by Crime Characteristics

Figure 5: Stacked Triple Differences Event Studies: Heterogeneous Analysis

Notes: This figure shows stacked triple-differences estimates from equation (1) on the impact of hate crimes on Hispanic voters. All regressions include voter fixed effects and census tract-year fixed effects. Panel A explores the impact across different voter demographics, including gender, age (above median as old below median as young), and party affiliation. In Panel B, we examine the effects based on crime characteristics such as gender, age (above median as old below median as young), and crime location (public places, residences, and businesses). Standard errors are clustered at the census tract level.

Figure 5 presents a heterogeneous analysis that reveals nuanced patterns in the relationship between hate crimes and voter turnout across various voter and victim characteristics, as well as crime locations. This granular examination uncovers significant variations in political responses to hate crimes.

Panel A, which focuses on voter demographics, demonstrates generally consistent positive effects across different segments of the electorate. While we observe slightly more pronounced responses among female voters compared to male voters, and marginally stronger effects among younger voters relative to older voters, these differences are not statistically significant at conventional levels. This consistency suggests a relatively uniform mobilizing effect of hate crimes on voter turnout across demographic characteristics. Notably, Democratic voters exhibit a robust positive response with a 1.6 pp increase in turnout, while Republican voters show no significant response.

Panel B, which examines crime characteristics, reveals more substantial heterogeneity. The gender of the victim appears to have little differential impact on voter turnout, with similar effects observed for both male and female victims. However, the age of the victim emerges as a significant moderator. Hate crimes against older individuals generate a stronger reaction compared to those against younger victims (2.4 vs. 0.8 pp). This could potentially be attributed to the perception of greater vulnerability among older community members who are more integrated into their neighborhoods. The location of the hate crime also emerges as a crucial factor: incidents in public places and businesses significantly increase turnout by 1.8 pp each, while crimes in residential areas have no significant impact. This pattern suggests that hate crimes in public spaces may be perceived as more salient threats to community safety, thereby eliciting a stronger electoral response.

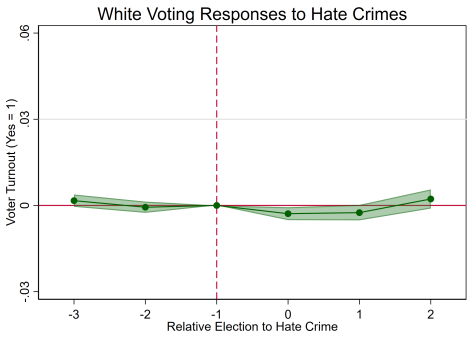
These heterogeneous effects provide valuable insights into the mechanisms through which hate crimes influence political behavior. Our findings indicate that the impact of hate crimes on voter turnout is not uniform across all segments of society or all types of incidents. Instead, certain demographic groups - particularly Democratic voters - appear more responsive to these events in terms of their political engagement. Similarly, the characteristics of the crime itself, especially its location and the age of the victim, play a significant role in determining the strength of the political response.

These results have important implications for understanding community resilience and

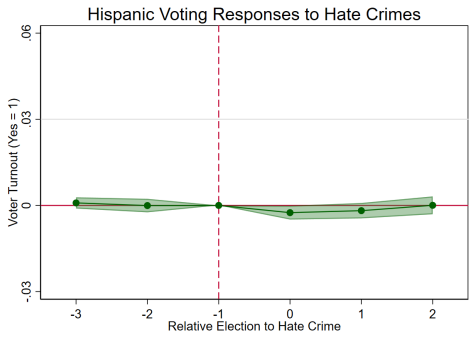
political mobilization in the face of discriminatory violence. They underscore the complex interplay between social identity, perceived threat, and political action, contributing to a more nuanced understanding of how hate crimes shape electoral participation in diverse communities.

4.4 Spillover Effects of Hate Crimes on Non-targeted Groups

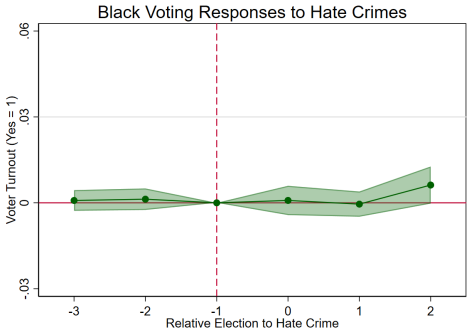
Having examined the direct impacts of hate crimes on targeted communities, we now investigate potential spillover effects on non-targeted racial groups. Through a complementary difference-in-differences analysis, we explore how various racial groups respond to hate crimes targeting other groups. Understanding these spillover effects is critical for interpreting our baseline findings comprehensively and determining if the political mobilization we observe is a targeted response to victimized communities or reflects broader changes in political participation across racial groups.



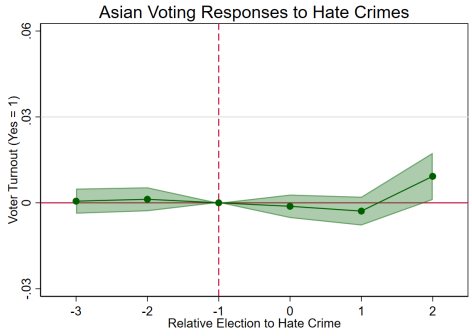
Panel A: White Voters' Response



Panel B: Hispanic Voters' Response



Panel C: Black Voters' Response



Panel D: Asian Voters' Response

Figure 6: Effects of Hate Crimes on Non-targeted Voters

Notes: This figure presents stacked difference-in-differences estimates and 90% confidence intervals for the effects of hate crimes on non-targeted voters. Panel A examines the impact of anti-Hispanic, anti-Black, and anti-Asian hate crimes on white voters. Panel B looks at the impact of anti-Black and anti-Asian hate crimes on Hispanic voters. Panel C studies the impact of anti-Hispanic and anti-Asian hate crimes on Black voters. Panel D investigates the impact of anti-Hispanic and anti-Black hate crimes on Asian voters. Nearby voters are defined as those who live within 0.3 miles of a hate crime. Standard errors are clustered at the census tract level.

Figure 6 presents event study estimates examining how different racial groups respond to hate crimes targeting other groups. Panel A shows that white voters exhibit no discernible change in political participation following hate crimes targeting minority groups. The estimated coefficients are precisely estimated around zero, with no discernible trend either before or after hate crime incidents. This pattern remains consistent regardless of which minority group is targeted.

Similarly, we find limited evidence of cross-group spillovers among minority communities. Panel B demonstrates that Hispanic voters maintain stable turnout patterns following anti-Black or anti-Asian hate crimes. Panel C indicates that Black voters' participation remains unchanged after anti-Hispanic and anti-Asian incidents. Panel D reveals no significant shifts in Asian voters' turnout following anti-Hispanic and anti-Black hate crimes.

These null findings provide valuable insights into the localized nature of political responses to discriminatory violence. The absence of significant spillover effects suggests that hate crimes generate highly specific political responses within targeted communities rather than inducing broader changes in political participation across racial groups. This targeted mobilization pattern highlights how discriminatory violence can reshape political engagement through its direct impact on affected communities, while having limited influence on the broader political landscape. These findings help us better understand the mechanisms through which hate crimes influence local political dynamics.

5 Mechanism

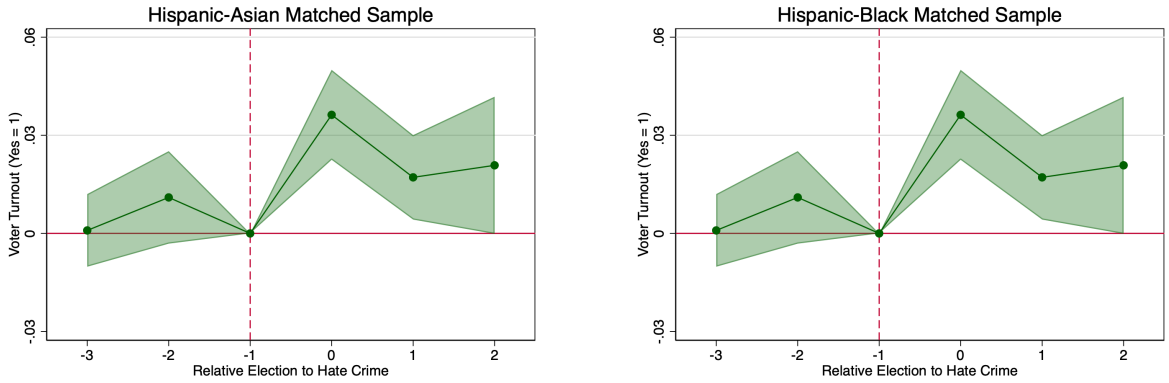
Having established the baseline effects of hate crimes on voter turnout, particularly among Hispanic voters, we now turn to exploring the potential mechanisms driving these results. Given the stark contrast in political mobilization effects across different minority groups, understanding the underlying mechanisms is crucial for interpreting our findings.

5.1 Individual-Level Heterogeneity

We first investigate whether the differential responses stem from systematic differences in voter characteristics. One potential explanation is that Hispanic voters differ systematically from Black and Asian voters in terms of socioeconomic status and political preferences, which could drive the heterogeneous mobilization effects.

To test this hypothesis, we conduct two separate matching analyses. First, we match Hispanic voters to Asian voters, and then separately to Black voters, based on key socioeconomic and political characteristics: education level (high school completion or above), income (median), party affiliation (Democratic), and age cohort (within three-year bands). For each matching exercise, we allow up to eight Hispanic matches per Black or Asian voter to maximize statistical power, with observations weighted by the inverse of match counts to maintain sample balance.

Figure 7 presents the event study estimates using these matched samples. Panel A shows the results when Hispanic voters are matched to Asian voters, while Panel B displays results for Hispanic voters matched to Black voters. In both cases, we continue to observe significant mobilization effects among Hispanic voters that closely mirror our baseline estimates, even after ensuring comparable individual characteristics. The consistency of these results across both matched samples suggests that the stronger political response among Hispanic voters cannot be explained by differences in individual voter characteristics alone.



Panel A: Hispanic-Asian Matched Sample

Panel B: Hispanic-Black Matched Sample

Figure 7: Event Study Estimates Using Matched Samples

Notes: This figure presents event study estimates using matched samples of Hispanic voters. Panel A shows results when Hispanic voters are matched to Asian voters, while Panel B shows results when Hispanic voters are matched to Black voters. Matching is based on education level, income, party affiliation, and age cohort. For each Black/Asian voter, up to eight Hispanic voters are matched, with observations weighted by the inverse of match counts. The shaded areas represent 90% confidence intervals, with standard errors clustered at census tract level.

Given that individual-level differences do not appear to drive the heterogeneous responses, we turn our attention to contextual factors that might facilitate collective political action. Specifically, we explore three potential mechanisms: community density and information dif-

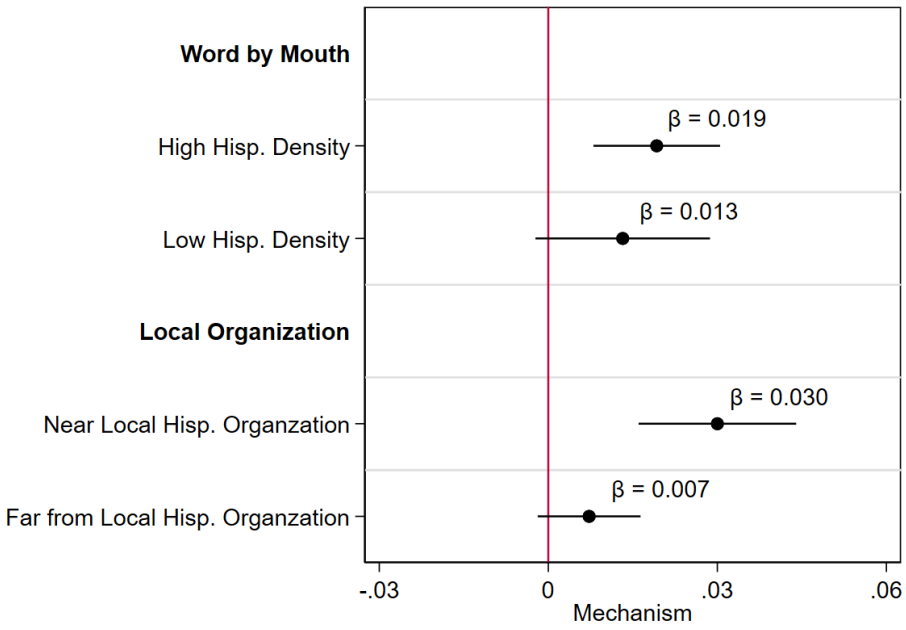
fusion through word of mouth, the role of local advocacy organizations, and media coverage. These contextual factors may help explain why similar individual characteristics translate into different political responses across racial groups.

5.2 Word of Mouth

People tend to discuss hate crimes that occur in their local area. Our first hypothesis posits that information about hate crimes primarily spreads through word of mouth within Hispanic communities. To test this hypothesis, we stratify our sample based on the Hispanic population density in each hate crime's census tract area. Specifically, we divide our sample into high and low Hispanic density areas using the median (i.e., 45.1%) as the threshold.

The top panel of Figure 8 presents the results of this analysis. We observe a non-trivial difference in the effect of hate crimes on voter turnout between high and low Hispanic density areas. In census tracts with above-median Hispanic population density, hate crimes increase voter turnout by 1.9 pp among nearby Hispanic voters. Conversely, areas with below-median Hispanic density show a smaller and statistically insignificant effect. This pattern provide suggestive evidence that word of mouth may play a crucial role in disseminating information about hate crimes and mobilizing voters in the local community. In areas with higher concentrations of Hispanic residents, the information is likely to spread more quickly and widely through social networks, leading to a more pronounced political response.

Figure 8: Potential Mechanism



Notes: This figure presents heterogeneous stacked triple-differences estimates from equation (1) on the impact of hate crimes on Hispanic voters. All regressions in our analysis incorporate voter fixed effects, and census tract-election fixed effects. The top panel examines the heterogeneous impact across areas with high and low Hispanic population density. The bottom panel analyzes the heterogeneous effects based on the median distance of hate crime to local Hispanic advocacy and community service organizations. The standard errors are clustered at census tract level.

5.3 Role of Local Advocacy Organizations

Our second hypothesis focuses on local Hispanic advocacy and community service organizations. These organizations provide essential services to local communities and have long-term relationships, trust, and roots in the communities they serve. A survey by Independent Sector (2024) reveals that 57% of respondents trust nonprofits, ranking them higher than government, business, and media in terms of public trust. Therefore, local organizations, with their close ties to the community, are uniquely positioned to disseminate information and mobilize voters in response to hate crimes.

To investigate this mechanism, we leverage data on Hispanic advocacy and community service organizations compiled by Kim (2022). Kim (2022) created the dataset using four directories: the *Encyclopedia of Associations – National Organizations of the U.S.*, the *Encyclopedia of Associations – Regional, State, and Local Organizations of the U.S.*, the *National Directory of Nonprofit Organizations*, and the *National Center for Charitable Statistics*. The dataset includes 519 Hispanic organizations in the U.S., with 46 located in Los Angeles County. We compute the minimal distance between hate crime incidents and these organizations, conducting a subsample analysis by classifying our sample based on proximity to local Hispanic organizations. Using the median distance (i.e., 2.3 miles) as the threshold, we classify areas as "near" or "far" from these organizations.

The bottom panel of Figure 8 presents the results. In areas close to Hispanic advocacy organizations, there is a 3 pp increase in voter turnout among nearby Hispanic voters compared to White counterparts following hate crimes. On the other hand, areas far from such organizations show a smaller and statistically insignificant effect.

This finding highlights the crucial role that local minority organizations play in mobilizing voters. Despite the prevalence of local minority organizations in U.S. society and their efforts in serving the community, their role in mobilizing minority voters and narrowing the racial political participation gap has been largely overlooked in the literature. Our results suggest that, in the face of community crises such as hate crimes, local Hispanic organizations likely act as crucial intermediaries, rapidly spreading awareness about hate crime incidents, organizing community responses, and facilitating get-out-the-vote efforts. [18] This mechanism highlights the importance of civil society infrastructure in mediating the relationship between

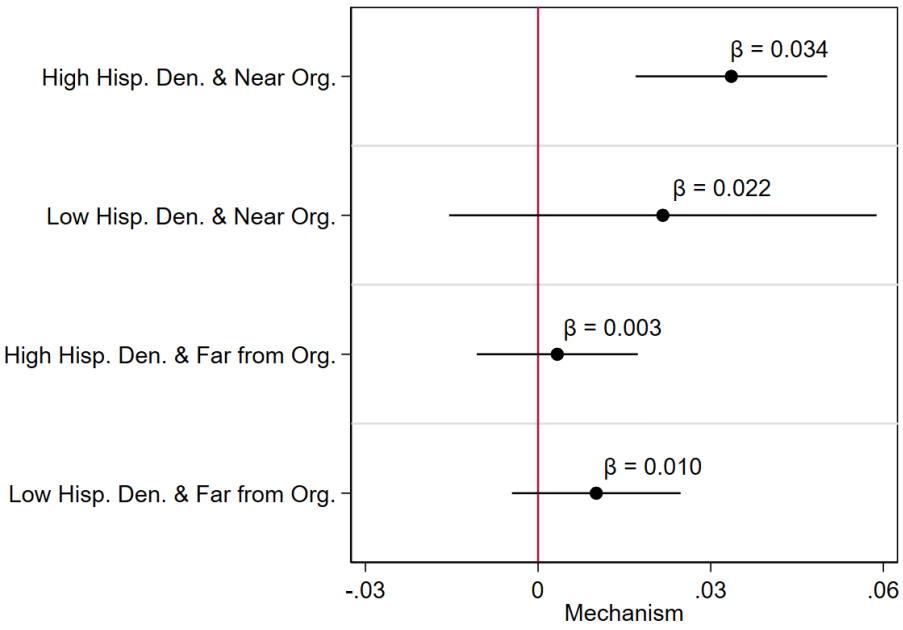
[18] For example, see: https://unidosus.org/issues/civil-rights-and-racial-equity/

discriminatory events and political behavior, contributing to a growing literature on the role of community organizations in political mobilization while offering novel insights into how such organizations can shape responses to discriminatory violence.

5.4 Density-Organization Interaction

While our previous analyses examined the roles of Hispanic population density and proximity to advocacy organizations separately, these factors are likely interrelated. Areas with higher concentrations of Hispanic residents may also be more likely to have established advocacy organizations. To disentangle these effects and identify potential synergies, we conduct a more granular analysis by partitioning our sample into four groups based on both Hispanic population density and proximity to advocacy organizations.

Figure 9: Mechanism Interaction



Notes: This figure presents heterogeneous stacked triple-differences estimates from equation (1) on the impact of hate crimes on Hispanic voters, examining the interaction between Hispanic population density and proximity to advocacy organizations. The sample is divided into four groups based on these two factors: high/low Hispanic population density (above/below median) and near/far from Hispanic advocacy organizations (above/below median distance). All regressions incorporate voter fixed effects and census tract-election fixed effects. The standard errors are clustered at census tract level.

Figure 9 presents the estimated effects for each of these four subgroups. The results

reveal a clear pattern: the mobilizing effect of hate crimes on Hispanic voter turnout is most pronounced in areas characterized by both high Hispanic population density and proximity to advocacy organizations (β = 0.034). This effect is substantially larger than in areas with only one of these characteristics present. Similarly, areas near advocacy organizations but with low Hispanic density exhibit a moderate effect, though this estimate is less precise. Areas with high Hispanic density but far from advocacy organizations show a markedly smaller and statistically insignificant effect. Lastly, areas with both low Hispanic density and distance from advocacy organizations show a small and insignificant effect.

These findings suggest a powerful complementarity between community structure and organizational resources in facilitating political mobilization in response to hate crimes. The presence of a dense Hispanic population likely enhances information diffusion and community cohesion, while nearby advocacy organizations can provide the institutional support and resources necessary to channel community sentiment into concrete political action. This interaction effect may explain why some communities exhibit stronger political responses to hate crimes than others. It underscores the importance of both informal social networks and formal organizational structures in translating the shock of discriminatory violence into increased civic engagement.

Our results also speak to the broader literature on social capital and collective action Ostrom (2015); Guiso, Sapienza and Zingales (2011). They suggest that the combination of dense social ties and formal organizational capacity can be particularly effective in overcoming the collective action problems inherent in political mobilization, especially in response to external threats. These findings have important implications for understanding the conditions under which minority communities can effectively respond to discriminatory violence through democratic channels. They suggest that efforts to enhance political participation among marginalized groups may be most effective when they simultaneously strengthen community bonds and support the development of local advocacy organizations.

5.5 Media Coverage

While word of mouth and local organizations appear to be significant channels, we also consider the potential role of media coverage in disseminating information about hate crimes. Following Ang and Tebes (2023), we conduct a comprehensive search of hate crime-related news in six major local newspapers: the Los Angeles Times, Los Angeles Daily News, Pasadena

Star News, San Gabriel Valley Tribune, Torrance Daily Breeze, and Whittier Daily News.[19]

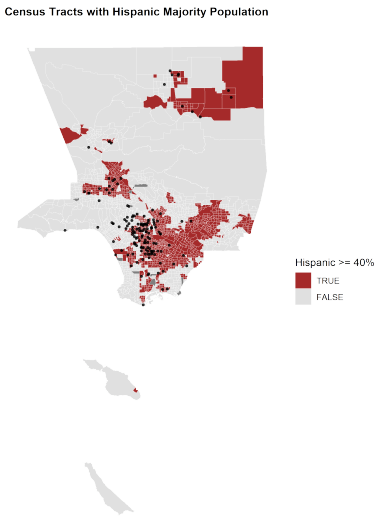
Our search yields 22 news articles related to hate crimes targeting minorities between 2014 and 2022. Of these, twelve concern anti-Black hate crimes, eight are about anti-Asian hate crimes, and two are related to White supremacy.[20] We are able to match approximately half of these reported incidents to our LACCHR hate crime data based on details such as date, location, and targeted group. However, only six of these matched incidents are classified as Part I crimes, which are included in our main analysis.

Importantly, the rate at which our sample hate crimes are mentioned in local newspapers is extremely low, at approximately 1.25%. This finding suggests that media coverage is unlikely to be a primary mechanism for information dissemination about hate crimes in our study context. The limited media attention to these incidents reinforces the importance of the other two mechanisms we identified: word of mouth and local advocacy organizations.

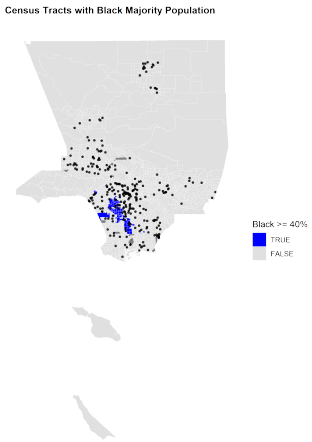
5.6 Explaining Heterogeneous Mobilization Effects

The stark contrast in political mobilization effects across different minority groups—with significant responses among Hispanic voters but limited effects among Black and Asian communities—warrants deeper investigation. We propose that the effectiveness of information diffusion through community networks plays a crucial role in explaining these heterogeneous responses.

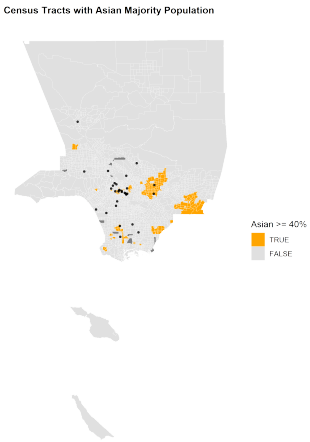
[19] We used the keywords "hate crime," "hate incident," and "hate" combined with specific ethnicities or races.
[20] Additionally, there are 10 news reports on anti-Jewish hate crimes.



Panel A: Hispanic Population Concentration



Panel B: Black Population Concentration



Panel C: Asian Population Concentration

Figure 10: Geographic Distribution of Minority Population Concentration and Hate Crimes

Notes: This figure presents the spatial distribution of minority population concentration and corresponding hate crimes in Los Angeles County. Each panel maps census tracts where the respective minority group comprises over 40% of the population (colored areas) and the locations of hate crimes targeting that group (black dots). Panel A shows Hispanic-majority areas (red) and anti-Hispanic hate crimes. Panel B displays Black-majority areas (blue) and anti-Black hate crimes. Panel C illustrates Asian-majority areas (orange) and anti-Asian hate crimes.

Figure 10 provides further evidence for the community network mecha ·nism by illustrating the spatial relationship between minority population concentration and hate crime occurrences. Panel A reveals that anti-Hispanic hate crimes frequently occur within or near census tracts with high Hispanic population density (above 40%). This geographic overlap cre-

ates conditions conducive to rapid information dissemination through community networks, facilitating collective political responses. The extensive clustering of Hispanic-majority areas (shown in red) suggests the presence of dense social networks that can effectively transmit information about discriminatory incidents.

In contrast, Panels B and C show markedly different patterns for Black and Asian communities. Black-majority census tracts (shown in blue) exhibit more limited clustering, and anti-Black hate crimes often occur in areas with lower Black population density. Similarly, Asian-majority areas (shown in orange) are relatively dispersed, with anti-Asian hate crimes frequently occurring outside these population centers. This geographic dispersion may impede the formation of dense community networks necessary for effective information transmission and collective political mobilization.

While our analysis of local advocacy organizations focuses primarily on Hispanic community organizations due to data limitations—comprehensive data on Black and Asian community organizations are not available—the observed pattern suggests a potential complementarity between population density and institutional infrastructure. The presence of Hispanic advocacy organizations in areas of high Hispanic population concentration likely amplifies the effectiveness of informal communication networks. The lack of comparable organizational data for Black and Asian communities prevents us from conducting a parallel analysis, but this data limitation itself points to potential differences in institutional infrastructure across minority groups that may contribute to the heterogeneous political responses we observe.

These findings underscore how the spatial organization of minority communities, potentially reinforced by institutional support networks, can fundamentally shape their capacity for collective political response to discriminatory violence. The effectiveness of informal information networks appears contingent on the geographic concentration of minority populations, suggesting that community density—along with supporting institutional infrastructure—plays a crucial role in translating discriminatory incidents into political mobilization.

6 Other Political Responses

6.1 Policy Preference

Experiencing serious hate crimes within local communities may be associated with shifts in policy preferences and could potentially serve as an underlying factor motivating people to turn out to vote. To better understand the political consequences of hate crimes, we examine whether such crimes are linked to changes in voters' policy preferences, particularly in relation to combatting crime and affirmative action.

6.1.1 Proposition 47 (2014) and Proposition 57 (2016)

First, we examine the effect of hate crimes on voters' policy preferences regarding criminal justice reform, as reflected by shifts in their choices on Proposition 47 in 2014 and Proposition 57 in 2016.These propositions both aimed to reduce penalties for certain non-violent offenses and reform the parole system. To understand how hate crimes are associated with voter support for these public policies, we employ the following difference-in-differences specification that accounts for hate crime events occurring between Proposition 47 and Proposition 57:

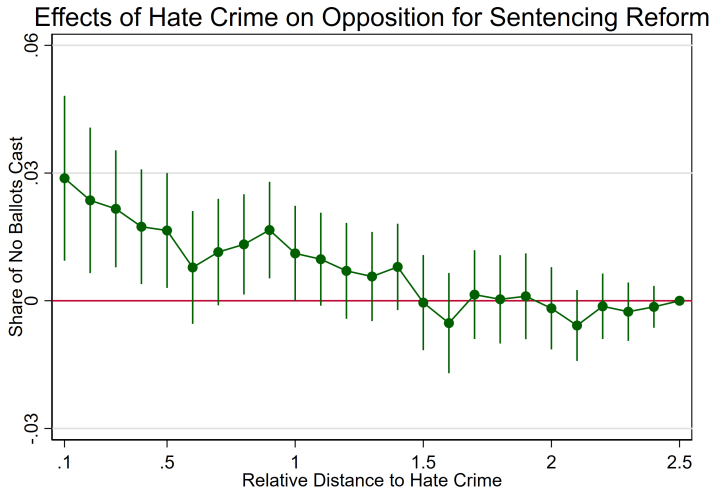
$$Y_{bt} = \alpha \cdot \text{Post}_t + \sum_d \gamma_d \cdot \text{Dist}_{b(d)} + \sum_d \eta_d \cdot \text{Post}_t \cdot \text{Dist}_{b(d)} + \lambda_b + \epsilon_{bt} \tag{5}$$

where $Y_{b,}$ measures the share of "No" votes at the census block level b. $\sum_d \text{Dist}_{i(d)}$ represents a set of mutually exclusive treatment indicators that measure the distance from the geometric center of a census block to the location of the nearest anti-Hispanic hate crime occurring between November 2014 and November 2016. Post_t is a dummy variable indicating year 2016.[21] We also control for census block fixed effects, λ_b, to ensure that the comparison of policy preferences is made within the same census block. Standard errors are clustered by census tract level.

The coefficients η_d in Figure 11 reveal a clear pattern: voters living closer to hate crime locations were more likely to shift from supporting the relaxation of the crackdown on crime

[21]Since individual vote choices are confidential, we are unable to further break down voting preferences by racial or ethnic groups. However, with 48.0% of the population in Los Angeles County being Hispanic, it is reasonable to assume that our approach reflects the policy preference changes of Hispanic voters to a considerable extent.

Figure 11: Effects on Opposition to Sentencing Reform



Notes: This figure reports distance-based estimates of the effects of hate crimes on the share of "no" votes, as derived from equation (6). The dataset is constructed using hate crime events that occurred between November 2014 and November 2016, and census tract fixed effects are incorporated into the analysis. Standard errors are clustered at the census tract level.

in 2014 to opposing it in 2016. For those living within 0.1 miles of the hate crime, we observe a 3 percentage point increase in "No" votes. This shift in policy preference diminishes as the distance from hate crime locations increases, but the geographic impact is more extensive compared to its effect on voter turnout. Taken at face value, both the magnitude and the geographic distance suggest that the changes in observed voter choices can be explained not only by increased voter turnout, but also by shifts in voters' policy preferences.

The increased opposition to sentencing reform in hate crime-affected areas suggests that these incidents heighten concerns about public safety and may lead to more punitive attitudes. This response could be interpreted as a defensive reaction, with voters seeking stronger law enforcement and stricter penalties as a means of protection against perceived threats.

6.1.2 Proposition 19 (2020)

Next, we analyze voters' policy preferences on affirmative action. Proposition 209, passed in 1996, banned the use of race- and gender-based affirmative action in California's public sector and public university admissions. Bleemer (2022) demonstrates that Proposition 209 led underrepresented minority freshman applicants to enroll in lower-quality colleges, which subsequently resulted in lower average wages later in life, with Hispanic applicants being most

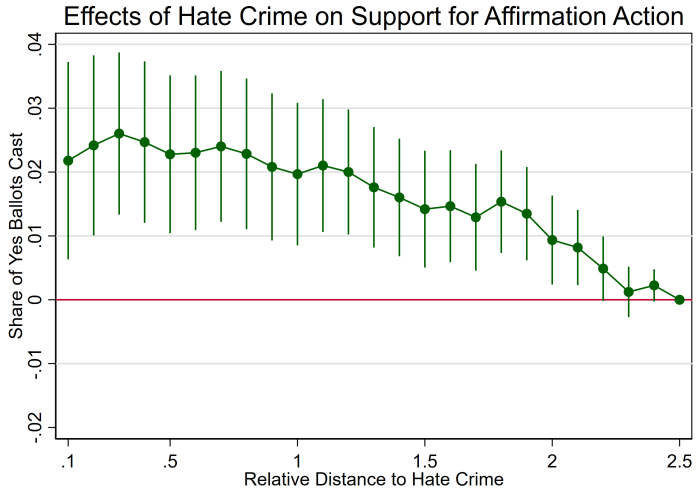
affected.

California Proposition 16 (2020) aimed to repeal Proposition 209 and reinstate affirmative action in the state's public sector and public university admissions. Considering the positive impact of affirmative action on Hispanic students, we expect Hispanic voters to be more likely to support Proposition 16, and this may be especially true for those living in close proximity to anti-Hispanic hate crimes. For this analysis, we estimate the following equation using anti-Hispanic hate crime events that occurred within one year prior to the Proposition 16 vote:

$$Y_b = \sum_d \gamma_d \cdot \text{Dist}_{b(d)} + \gamma X_b + \lambda_n + \epsilon_b \tag{6}$$

Here, Y_b represents support for affirmative action at the block level. The main independent variable of interest is $\text{Dist}_{b(d)}$, which consists of exclusive treatment indicators that measure a block's distance to the hate crime. We include an extensive list of census-block level controls, including population, male ratio, Hispanic ratio, and the number of crimes. We further include census tract fixed effects: λ_n, and cluster our standard errors at the census tract level.

Figure 12: Effects on Support for Affirmation Action



Notes: This figure reports distance estimates of the effects of hate crime on share of yes Ballots Cast based on equation (6). We construct the stacked dataset using hate crime events that occurred within one year before Proposition 16, while also incorporating census tract fixed effects in our analysis. The standard errors are clustered at census tract level.

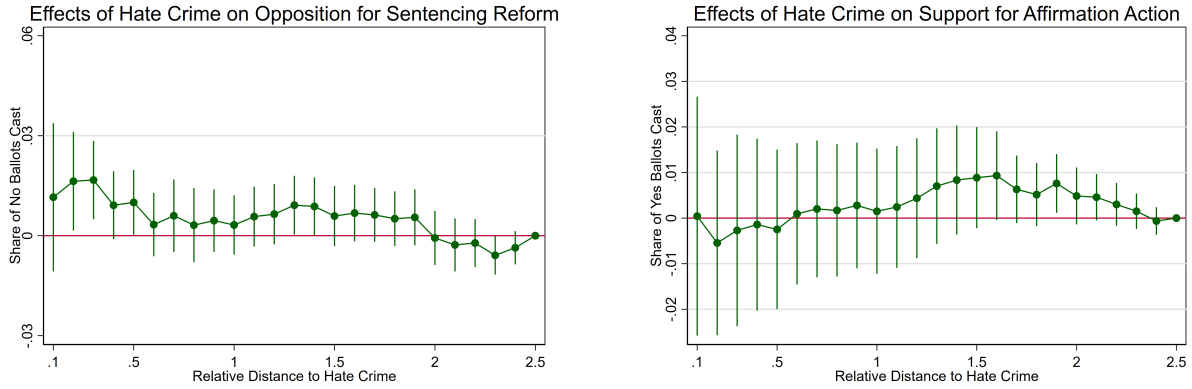
The results presented in Figure 12 show a marked increase in support for affirmative action in areas closer to hate crime incidents. The share of "Yes" votes is higher in proximity to hate crime locations, with the effect gradually declining as distance increases. The increased support for affirmative action in areas affected by hate crimes likely reflects a heightened awareness of racial and ethnic disparities, driven by personal or community experiences of discriminatory violence. This awareness seems to translate into concrete political action, as voters mobilize to support policies aimed at addressing these systemic issues.

These findings offer a deeper understanding of the mechanisms behind the increased voter turnout observed in our earlier analysis. The surge in political participation appears to be driven, at least in part, by two potentially complementary policy demands: enhancing community safety, and advancing greater equality and opportunity. These multifaceted responses illustrate the intricate ways in which hate crimes impact political attitudes and behavior.

6.1.3 Placebo Test

For Propositions 47 and 57, we use hate crime events from two years later (2017-2018) as a placebo. Similarly, for Proposition 16, where we originally analyzed crime events from the year leading up to Proposition 19, we perform a placebo test using crime events from the year following Proposition 19. The logic behind these tests is straightforward: if our identification strategy is valid, future hate crime events should not affect past voting behavior.

Figure 13: Placebo Test on Policy Preference



Panel A: Share of No Ballots Cast Panel B: Share of Yes Ballots Cast

Notes: This figure reports stacked difference-in-differences and distance estimates of the effects of hate crime based on equation (5). We construct the stacked dataset using hate crime events within two years after Proposition 57, while also incorporating census tract fixed effects in our analysis. Panel A displays the effect of distance from hate crimes on Share of No Ballots Cast for sentencing reform while Panel B presents its effects on Share of Yes Ballots Cast for affirmation action. The standard errors are clustered at census tract level.

Panel A of Figure 13 present the results of the placebo tests for opposition to sentencing reform (Propositions 47 and 57). It displays a distinct pattern compared to Figure 11. Unlike the clear decrease in effect over distance seen in Figure 11, it shows a relatively stable higher support for combatting crime over the distance, though the magnitude is substantially smaller. This may reflect the fact that hate crimes are correlated with overall crime in a larger geographic area, and people living in areas with higher crime rates are more likely to support measures to combat crime, even though the specific location and timing of hate crimes may be exogenous. Panel B of Figure 13 illustrates the placebo test results for support of affirmative action (Proposition 16), showing no discernible pattern or statistically significant effects across various distance bands from future hate crime locations.

These placebo tests address potential concerns about confounding factors or anticipation effects. If areas more prone to hate crimes were systematically different in their policy preferences for reasons unrelated to specific hate crime events, we would expect to observe a similar pattern in these placebo tests. The absence of such a pattern strengthens our interpretation that the shifts in policy preferences observed in our main analysis are responses to hate crime events, rather than reflections of underlying differences in census blocks or pre-existing political attitudes.

6.2 Candidate Entry

Descriptive representation plays an important role in policy decisions (Chattopadhyay and Duflo, 2004; Beach and Jones, 2017; Fischer, 2023; Beach et al., 2024). While Zonszein and Grossman (n.d.) finds that the number of hate crimes increase by 67% increase in constituencies in which minority candidates narrowly win versus narrowly lose in the United Kingdom, we pose the opposite question: could a serious hate crime result in more candidates from the targeted group running for office and an increase in officials from that group?

We utilize data from the California Elections Data Archive (CEDA), which offers comprehensive details on local elections in California. This includes information such as election dates, offices, candidate names, occupations, incumbent status, and vote shares. Our study focuses on city council elections in Los Angeles County from 2004 to 2022. This dataset includes information from 88 cities and accounts for over 5,000 candidates who have contested city office positions during this period. On average, there are 2.5 White candidates, 2 Hispanic candidates, 1.1 Black candidates, and 1 Asian candidate running for each city council contest. Additionally, we integrate this electoral data with hate crime data from the Los Angeles County Commission on Human Relations (LACCHR) covering the period from 2003 to 2022, representing the most extensive dataset available for us.

We adopt a stacked triple-differences specification similar to the approach used by (Cengiz et al., 2019). Specifically, we construct 12 distinct datasets, each corresponding to an event year from 2008 to 2019. Each dataset includes treated cities that experienced serious hate crimes in year h but reported no serious hate crimes in the four years prior to year h.[22] Additionally, we include clean control cities, defined as those that did not experience any serious hate crimes in the four years before and after the event year h, totaling an eight-year span. Cities that do not meet these criteria are excluded from dataset. There are 27 cities designated as treated for anti-Hispanic hate crimes, 35 for anti-Black hate crimes, and 8 for anti-Asian hate crimes. This methodology ensures a robust comparison between affected cities and their control counterparts over the 8-years period. We estimate the following specification:

[22]The selection of a four-year span represents a compromise between the available sample period and the timing of local election cycles.

$$Y_{cgth} = \alpha \cdot \text{Post}_t \cdot \text{Targeted}_g + \beta \cdot \text{Treated}_c \cdot \text{Targeted}_g + \delta \cdot \text{Post}_t \cdot \text{Treated}_c + \boxed{\theta \cdot \text{Post}_t \cdot \text{Treated}_c \cdot \text{Targeted}_g} + \lambda_{th} + \zeta_{ch} + \epsilon_{cgth} \tag{7}$$

where Y_{crth} is either the number of candidates from ethnicity group g running for city office in city c during year t or the number of elected officials from ethnicity group g running for city office in city c during year t. Treated_c is a dummy variable indicating whether city c is a treated city in event h. Post_t is a dummy variable indicating whether the election occurred after the hate crime. Targeted_g equals 1 if the ethnicity group is the targeted group, and equals 0 for White. We control for election-year-event fixed effects (λ_{th}) and city-event fixed effects (ζ_{ch}).

Results are reported in Table 4. We find that, following an anti-Hispanic hate crime, the number of Hispanic candidates running for city office increases by 0.695, which represents a 34.75% rise in the number of Hispanic candidates. However, the increase in Hispanic candidates does not translate into a higher number of Hispanic officials. Moreover, we do not observe an increase in Black or Asian American candidates running for city office following anti-Black or anti-Asian hate crimes, respectively.

Table 4: Candidate Entry and Elected Officials

	(1)	(2)	(3)	(4)
	# of Candidates		# of Elected Officials	
Panel A: Hispanic				
Treated City*Post*Targeted Group	0.695*	0.695*	0.0759	0.0759
	(0.350)	(0.352)	(0.160)	(0.161)
Panel B: Black				
Treated City*Post*Targeted Group	0.299	0.299	0.148	0.148
	(0.200)	(0.201)	(0.127)	(0.127)
Panel C: Asian				
Treated City*Post*Targeted Group	0.253	0.253	-0.00478	-0.00478
	(0.412)	(0.413)	(0.153)	(0.153)
Event Year FEs	✓		✓	
City FEs	✓		✓	
Election FEs	✓		✓	
Event Year-Election FEs		✓		✓
Event Year-City FEs		✓		✓

Notes: This table presents the impact of hate crimes on candidate entry and the election of officials for Hispanic (Panel A), Black (Panel B), and Asian (Panel C), respectively. Outcome is defined as the number of candidates (Columns 1 and 2) and the number of elected officials (Columns 3 and 4). Standard errors are clustered at city level.

7 Conclusions and Future Directions

In this paper, we examine how targeted groups respond to hate crimes through electoral participation. By merging administrative data on hate crimes in Los Angeles County with individual voter files and turnout records, we leverage hyperlocal variations in the location and timing of hate crimes. Our analysis reveals that anti-Hispanic hate crimes lead to a 1.6 percentage point increase in voter turnout among nearby Hispanic voters. We also show that hate crimes are associated with changes in policy preferences, particularly around crime prevention and affirmative action. Additionally, hate crimes motivate more Hispanic candidates to run for local office. Notably, we find no similar shifts in voting behavior among Black or Asian American voters following anti-Black or anti-Asian hate crimes, respectively.

Beyond this paper, an important area for further exploration is understanding the broader impact of hate crimes on local communities. Many key outcomes remain underexplored. For instance, hate crimes may affect students' academic performance and mental health, particularly among Black and Hispanic individuals, who are frequently targeted. These consequences could potentially exacerbate the achievement gap between minority and White students. Another critical dimension is the effect on worker productivity, including how hate crimes impact employees and local firms. In terms of responses to hate crimes, our paper primarily focuses on formal electoral responses, which likely represent an important subset of broader community reactions. While many individuals lack citizenship and cannot vote, they can still participate in other forms of community engagement, such as protests. For example, many Asian communities in New York City protested against the rise of anti-Asian hate crimes during the COVID-19 pandemic. Future research could address these questions using robust research designs and reliable hate crime data to provide a more comprehensive understanding of the social consequences and responses. Moreover, it is crucial to focus on identifying effective strategies to mitigate the adverse effects of hate crimes and to combat these crimes in local communities.

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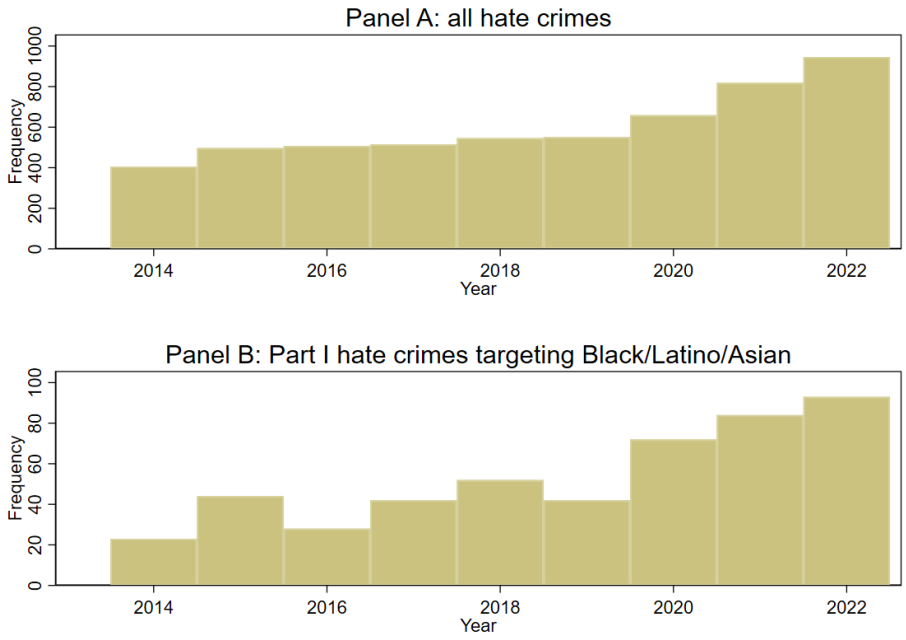
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Appendix

Figure A1: Hate Crimes in L.A. (Time Trend)



Notes: Panel A shows the time trend for all hate crimes in Los Angeles County from 2014 to 2022. Panel B displays the time trend for all Part I hate crimes targeting Black, Latino, and Asian populations in Los Angeles County over the same period.