Political Responses to Hate Crimes*

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Abstract: We investigate how targeted groups react politically to racially motivated hate crimes within their communities. Combining incident-level administrative data on hate crimes in Los Angeles County from 2014 to 2022 with individual voter files, we exploit the hyperlocal variation in the geography and timing of these crimes. We find that serious anti-Hispanic hate crimes increase voter turnout among nearby Hispanics by 1.6 percentage points compared to nearby Whites. Communities with dense Hispanic populations and Hispanic advocacy and community service organizations are primarily responsible for this mobilization effect. Moreover, we demonstrate that hate crimes are associated with shifts in voters' policy preferences, particularly in the areas of crime prevention and affirmative action. Despite this, we do not find any significant differences in political participation among Black and Asian American communities following anti-Black and anti-Asian hate crimes, respectively. Los Angeles County's large Hispanic population and extensive network of community organizations may play an important role in fostering mobilization.

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

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1 Introduction

In the U.S. penal code, perpetrators of hate crimes face harsher punishments in part because of the broader societal consequences (*Wisconsin v. Mitchell, 508 U.S. 476 (1993)*). Unlike typical criminal acts, hate crimes are committed with the intent to create fear and perpetuate a climate of hostility and exclusion among specific communities. These acts are far from rare: well over 11,000 incidents were recorded in the U.S. in 2023 alone (Dancygier and Green, 2010; Farrell and Lockwood, 2023).

In this paper, we study the broader political ramifications of hate crimes by studying their impact on democratic participation. The effects are ex ante ambiguous. Hate crimes could discourage civic participation; alternatively, they could spur collective action by motivating affected individuals to band together and assert their rights in response to these group threats. The interplay between mobilization and intimidation effects underscores the complexity of community responses to hate crimes, emphasizing the need for empirical evidence on this question.

Yet such evidence is limited, as disentangling these competing effects poses considerable data and methodological challenges. First, the FBI's Uniform Crime Reporting Program (UCR), which provides a major source of data on hate crimes, suffers from significant under-reporting. It also lacks detailed location data, making it unsuitable for most rigorous research (Kaplan, 2021). Additionally, hate crimes often correlate with various socio-economic factors that can influence political participation, including economic conditions and rates of non-bias-motivated crimes.

To address the challenges of data reliability and granularity, we utilize a unique incident-level administrative dataset compiled by the Los Angeles County Commission on Human Relations (LACCHR) from 2014 to 2022. The LACCHR has been tracking hate crimes since 1980 and draws on information from a variety of sources, including law enforcement agencies, educational institutions, community organizations, and direct reports from victims. LACCHR reviews each reported incident independently using consistent standards. As a crucial aspect of identification, this dataset provides precise geolocation data for each hate crime, which enables us to detect highly localized exposures to these crimes. In addition to reducing concerns about under-reporting of hate crimes (Kena and Thompson, 2021), we conduct our analysis primarily based on Part I offenses – serious crimes such as murder, aggravated assault, and

robbery. Considering the severity of these crimes, they are less likely to be underreported, but also have a greater potential impact on the response of the community.

In order to overcome the identification challenges arising from the correlation between hate crimes and socio-economic factors, we rely on an empirical strategy based on hyperlocal variation in the geography and timing of hate crimes. As part of our approach, we compare changes in political participation over time among voters living very close to a hate crime incident (within 0.3 miles) with those living somewhat further away (0.3 to 1.5 miles), but still within the same neighborhood. As a result, we are able to take into account localized socio-economic factors and trends that may have an impact on political participation. This strategy is based on the observation that most hate crimes receive little media coverage and generally spread within the local community. In addition, hate crimes tend to target specific groups, which allows us to compare the political participation of voters from these groups with that of White voters before and after the occurrence of hate crimes. The three sources of variation in exposure to hate crimes – location, timing, and targeted group – enable us to separate the specific effects of hate crimes from broader reactions to local criminal activity or other confounding factors.

Voter turnout in general elections is our primary outcome of interest. In order to link hate crime exposure to individual voter turnout data, we combine the hate crime data with the voter file at the individual level, which contains snapshots of all registered voters in Los Angeles County from 2014 to 2024. The results of our analysis indicate that anti-Hispanic hate crimes significantly increase Hispanic voter turnout in the surrounding area. This mobilization effect shows a notable spatial decay, with the strongest effect occurring within 0.3 miles of the location of the hate crime and diminishing thereafter. In addition, the event study plot reveals that the effect is most pronounced in the general election immediately following the incident. On average, anti-Hispanic hate crimes result in an increase in Hispanic turnout of 1.6 percentage points nearby – corresponding to a reduction of 17% in the racial turnout gap. Accordingly, our findings indicate that this electoral response is a reflection of changes in political behavior rather than demographic shifts since we do not observe any evidence of selective migration or voter registration. There are no significant spillover effects on non-targeted racial groups, suggesting that hate crimes are accompanied by highly specific political responses within victimized communities. In contrast, we do not observe similar mobilization effects within Black or Asian American communities following hate crimes targeting their

groups. Thus, the political response to hate crimes may be context-specific.

In order to explain the mechanism behind these effects, we first examine whether individual-level characteristics are responsible for the heterogeneous responses across racial groups. By using matched samples of Hispanic voters who mirror the socioeconomic and political characteristics of Black and Asian American voters, we find that the mobilization effect persists, suggesting that contextual factors are more important than individual characteristics in explaining the differential responses. Following this, we examine three key contextual factors: community density, institutional infrastructure, and media coverage. We find that the mobilization effect is more pronounced in areas with a high Hispanic population density and a strong presence of Hispanic advocacy organizations, with the strongest effects occurring in areas where both factors are present. In our sample, there is limited media coverage of hate crimes, suggesting that local media has a minimal impact on these outcomes. In accordance with this interpretation, we find that anti-Black and anti-Asian hate crimes frequently occur in areas with lower concentrations of these populations. As a result of this weaker community network, there may not be any political mobilization effects for these groups.

Beyond voter turnout, political responses to hate crimes can take many forms. To begin with, we observe significant shifts in policy preferences as reflected in voting patterns on state propositions. Following hate crimes, affected areas demonstrate increased opposition to reducing criminal penalties. These communities also demonstrate a higher level of support for affirmative action policies, indicating that hate crimes have the potential to raise awareness of systemic inequalities. Changes in policy preferences may also contribute to a higher turnout rate. Last but not least, we observe broader political engagement through the emergence of Hispanic candidates in cities experiencing hate crimes. Taking a broader perspective, the increase in descriptive representation indicates that hate crimes can serve as a catalyst for broader political participation within affected communities, underscoring how discriminatory violence can influence political preference and behavior.

This paper contributes to the literature in two important ways. To begin with, it directly adds to the growing body of research on hate crimes. While existing research primarily focuses on the causes of hate sentiment and hate crimes, highlighting the importance 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,

2024), 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. A critical aspect of understanding hate crimes lies in examining their consequences. While they are widely recognized as "message crimes," their broader implications—serving as a foundational justification for hate crime legislation—remain insufficiently explored in the literature (Lawrence, 1999; Jaskiewicz, 2023). Our analysis examines the significant political consequences of hate crimes in local communities, as well as the key factors driving community mobilization – group density and the role of local organizations. More broadly, our study examines the ways in which minority communities respond to public acts of discrimination and racism – a subject that is both broad in scope and fundamental to understanding race and inequality.

Second, this article contributes to a growing body of research on the impact of violence on electoral participation and policy preference. It explores how violence can influence an individual's engagement in democratic processes, including terrorist attacks (Berrebi and Esteban, 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 shootings and school shootings generally do not affect voter turnout rates at the county level; however, they influence voters' policy preferences regarding gun control and increase Democratic Party vote shares (Hassell, Holbein and Baldwin, 2020; Yousaf, 2021; Garcia-Montoya, Arjona and Lacombe, 2022). In the United States, violence against minority groups, such as historical lynchings of Black individuals, has been found to discourage Black voter participation both in the short and long term (Jones, Troesken and Walsh, 2017; Williams, 2022). In spite of the fact that police violence can increase voter registration and vote counts by 3%–5%, this effect is highly localized and is largely observed in 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 the mobilizing effects they have on minorities. In contrast to historical acts such as lynching, hate crimes do not discourage voters from participating in elections. As a matter of fact, their impact is more significant in both magnitude and geographic scope than that of police violence.

2 Data

Our analysis focuses on Los Angeles County, the most populous and most ethnically diverse county in the country. Based on the 2020 Census, Los Angeles County has over 10 million residents, 48.0% of whom identify as Hispanic, 25.6% as White, 15.0% as Asian, and 7.9% as Black.[1] The primary data sources for our analysis are two administrative datasets: an incident-level hate crime dataset provided by the Los Angeles County Commission on Human Relations (LACCHR), and a voter file provided by L2, which includes the universe of registered voters in Los Angeles County as well as their turnout records. We also included data on other political outcomes from a variety of sources, including 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

Data on hate crimes is provided by the Los Angeles County Commission on Human Relations (LACCHR). LACCHR was founded in 1944 in response to the "Zoot Suit Riots," with the objective of resolving intercultural conflicts and eliminating bias and prejudice throughout Los Angeles County. One of the key initiatives of LACCHR is the monitoring of hate crimes. Since 1980, the commission has been collecting data from over 100 law enforcement agencies, educational institutions, community-based organizations, and victims' direct reports through 211 LA. LACCHR reviews each reported hate crime to ensure consistency and accuracy.[2] Among the oldest and largest organizations of its type, LACCHR provides training on the identification and prevention of hate crimes to organizations of a similar nature.

The California Penal Code Section 422.55 defines a hate crime 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 orientation. Es-

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

[2] There are also LACCHR initiatives such as the annual Hate Crime Report, the quarterly Network Against Hate Crime Meetings, the LA vs Hate Anti-Hate Initiative, and the LA County Anti-Racism, Diversity, and Inclusion Initiative.

sentially, hate crimes are criminal acts motivated by bias or prejudice.[3]

This is an example taken from the *LACCHR 2018 Hate Crime Report*:

> *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.*

The dataset includes all hate crimes reported to LACCHR from 2014 to 2022, with a total of approximately 5,500 incidents. The data provides detailed information regarding dates, exact locations, bias motivations, offense types, and the demographic profiles of both victims and suspects.[4] Panel A of Figure A1 presents a time trend for all hate crimes reported in Los Angeles County over the past several years. In recent years, there has been an increase in hate crimes, in line with the rising trend observed in other parts of the country. Approximately 45.5% of these incidents targeted Black, Hispanic, or Asian individuals, while 19.6% were classified as Part I crimes, which included murder (2.5%), robbery (8.1%), and aggravated assault (86.5%). In our analysis, we focus primarily on Part I hate crimes due to their severity and lower likelihood of being underreported. Panel B of Figure A1 shows the time trend for all Part I hate crimes targeting Black, Hispanic, and Asian populations in Los Angeles County over the same period, following a similar pattern to that of all hate crimes.

The Black community is the most targeted group among these serious racially motivated hate crimes, accounting for 62.3% of all incidents. Anti-Hispanic bias is involved in 32.3% of cases, while 6.5% target Asians, with the majority occurring after the onset of COVID-19. In cases of anti-Black hate crimes, 61.2% of suspects are Hispanic, and in cases of anti-Hispanic hate crimes, 57.2% of suspects are Black. The proportion of white suspects involved in anti-

[3] Hate speech is also a closely related concept, which is prevalent on social media and is frequently sanctioned (Jiménez Durán, 2021). It is important to note, however, that hate speech is often not classified as a hate crime. Derogatory words or slurs directed at a protected class member, without an accompanying threat of violence, are considered hate incidents rather than crimes. Moreover, graffiti is classified as a hate crime only when it involves vandalism that targets and disparages a protected group.

[4] Utilizing Google Maps, we manually geocoded each address into longitude and latitude coordinates. For privacy reasons, the exact location of the hate crime is obfuscated by rounding the last two digits of the street number to "50." Based on the assumption that each unit represents a distance of 0.008 miles, this method introduces an error of approximately 0.1 miles in the exact location of the hate crime.

Black and anti-Hispanic hate crimes is 28.8% and 24.5%, respectively.

Figure 1 illustrates the geographic distribution of hate crimes targeting Black, Hispanic, and Asian American communities. The incidence of hate crimes is widespread throughout Los Angeles County, rather than concentrated in certain neighborhoods, although some areas experience higher incidences than others. The spatial variations, which may be related to local characteristics, motivate our method of identifying hate crimes, which leverages hyperlocal variations in their location and timing.

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

Notes: This figure depicts the spatial distribution of serious hate crimes from 2014 to 2022. The colored dots in each panel refer to hate crimes committed against Blacks, Hispanics, and Asians respectively.

2.2 Data on Voter Turnout

Our analysis is based on the California Historical Voter File (2014–2024) provided by L2, a nonpartisan vendor of voter registration data. This dataset contains snapshots of all registered

voters in Los Angeles County (and California) from 2014 to 2024, updated approximately four times annually.[5] Importantly, it provides precise residential addresses for each voter, allowing us to accurately measure the proximity of hate crimes to each voter's address in the same year. The voter file contains each voter's complete turnout history for all general elections from 2008 to 2022, thus enabling us to track their political participation over time. In addition, it contains detailed demographic information regarding voters, such as gender, age, and predicted ethnicity.[6]

Approximately 4.8 million voters were registered in Los Angeles County as of 2020. In terms of ethnicity, 43.8% of the voters identify as Hispanic, 37.4% as White, 11.2% as Asian American, and 7.7% as Black. There is a significant difference in turnout between these demographic groups. Turnout rates for Hispanic, White, Asian American, and Black registered voters in the 2020 presidential election were 71.1%, 80.3%, 75.1%, and 69.1%, respectively. Besides analyzing voter turnout, the voter file is also used to analyze migration patterns as well as trends in voter registration.

2.3 Data on Policy Preference

As no proposition directly relates to hate crimes, we analyse election data from three significant California propositions related to criminal offenses or affirmative action to determine the impact of hate crimes on policy preferences.

Proposition 47, referred to as the "Safe Neighborhoods and Schools Act" in 2014, reclassified certain nonviolent felonies as misdemeanors, particularly drug possession and theft crimes under $950. Specifically, this proposition aimed to reduce prison populations and redirect savings to crime prevention and support programs. 59.6% of the votes were cast in favor of the measure.

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

[5]Based on the availability of data, we use the voter file updated either in the first or second quarter of each year. Since our data acquisition occurred in early 2024, we do not possess turnout records for the 2024 general elections.

[6]In California, voters are not required to report their race and ethnicity. Therefore, L2 utilizes a sophisticated algorithm to predict race and ethnicity based on full names, census block data, and known marriage indicators. Our main findings remain unchanged when we 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). The results are presented in Table A1.

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 was passed with a majority of 64.5%.

Proposition 16 in 2020 sought to repeal Proposition 209 (passed in 1996), which prohibited state governmental institutions from considering race, gender, color, ethnicity, or national origin when hiring or awarding public contracts. California's Proposition 16 sought to reinstate affirmative action in the public sector. The measure was defeated with 57% voting against and 43% voting in favor.

With the California Statewide Database, we can obtain block-level estimates of the numbers of votes cast for and against each proposition, providing granular information for analyzing voting patterns across different communities.[7]

2.4 Data on Candidate Entry

The California Elections Data Archive (CEDA) provides information on candidates running for city elections in Los Angeles County.[8] This database contains information about local elections in California, such as election dates, offices, candidate names, occupations, incumbent status, and vote shares. This study focuses on Los Angeles County city council elections from 2004 to 2022. During the sample period, over 5,000 candidates ran for city offices in 90 cities, with approximately 1,900 of them being elected. The race and ethnicity of candidates are not available; therefore, we use the R package *rethnicity* to predict their race and ethnicity.[9]

3 Empirical Strategy

There is limited causal evidence regarding the impact of hate crimes on local communities. At least in part, this is because analyzing the correlation between hate crimes and neighborhood outcomes is confounded by the fact that hate crimes are more prevalent in disadvantaged areas with high rates of homicide and poverty. Additionally, minority participation in politics may, in itself, result in an increase in hate crimes (Zonszein and Grossman, 2024).

[7] https://statewidedatabase.org/.

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

[9] 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. The dataset, however, covers only the period between 2005 and 2011 and includes candidates who narrowly won or lost the election, making it particularly suitable for the close-election identification design.

Due to this, if we simply regress the occurrence of hate crimes on voter turnout, the results would likely be biased by geographic differences in socioeconomic conditions.

To address this issue, we exploit hyperlocal variation in exposure to hate crimes within neighborhoods similar to Ang (2021). In essence, our analysis compares changes in political participation over time among voters who reside very close to hate crimes with those who reside slightly further away yet still in the same neighborhood. Therefore, both groups are likely to share similar backgrounds and experience similar local conditions, except for the occurrence of hate crimes. The basis for this comparison is the observation that most hate crimes are virtually unreported by the media, suggesting their effects may be highly localized and geographically concentrated. Moreover, since hate crimes primarily target minority groups, minority voters can be compared to white voters to account for the overall trend in political participation within the local community. Our study integrates these three sources of variation in order to estimate the causal impact of hate crimes on voter behavior within local communities.

Our final analysis includes 480 serious hate crimes classified as Part I offenses, such as aggravated assaults, robberies, and murders. Out of these incidents, 155 targeted Hispanics, 299 targeted Blacks, and 31 targeted Asians. Our sample of voters is composed of both members of the targeted group as well as white voters residing within a 1.5-mile radius of the crime, and we observe their turnout in the three general elections both before and after each hate crime. As most local elections in California are held during election cycles, this approach also captures most local elections. In the case of individuals experiencing multiple incidents (i.e., hate crimes occurring on different days) during the study period, only the first incident is considered.

3.1 Graphical Evidence

Our empirical strategy begins by illustrating the spatial dynamics of hate crimes' impact on political participation through graphical evidence. Our hypothesis is that the effects of hate crimes on voter turnout diminish with increasing distance from the location of the incident. A stacked difference-in-difference-in-differences (DDD) specification is used to rigorously analyze this spatial heterogeneity. Using this approach, we are able to estimate the varying effects of hate crimes on targeted groups over a wide range of distances.

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

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 are used to measure the voter's distance from the hate crime (e.g., 0–0.1 miles, 0.1–0.2 miles, 0.2–0.3 miles). 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 measures the differential effect of hate crimes on turnout in targeted groups across different distance bands, in comparison to non-targeted groups and pre-hate crime periods. The specification provides an agnostic method for tracing the spatial decay of hate crimes' impact. Additionally, we incorporate voter fixed effects, φ_i, to account for individual characteristics, as well as census tract-election fixed effects, ζ_{ct}, in order to ensure that comparisons are made among individuals within the same neighborhood. The standard errors are clustered at the census tract level.[10]

For anti-Hispanic, anti-Black, and anti-Asian hate crimes, we estimate this model separately, generating graphs in Figure 2 that plot the estimated coefficients, β_d, against distance. Several nuanced patterns can be discerned in these figures regarding the spatial reach of hate crimes. Among Hispanic voters, we find significant mobilization effects that diminish with distance and disappear beyond 0.3 miles from the location of the hate crime, suggesting that these effects are relatively localized. In contrast, Black and Asian American voters do not show significant effects across varying distances.

These findings illustrate the spatial dynamics of hate crimes within local communities and provide guidance for defining treated distances in the subsequent empirical analysis. Accordingly, we refine our definition of nearby areas to a radius of 0.3 miles. Our data-driven

[10] According to the 2010 Census, Los Angeles County is divided into 2,344 census tracts. As a general rule, each census tract is designed to accommodate approximately 4,000 people and 1,600 housing units. An average census tract in Los Angeles County covers an area of approximately 1.7 square miles.

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 on voter turnout, while Panels B and C demonstrate the impact of hate crimes targeting Black and Asian. Standard errors are clustered at the census tract level.

methodology for defining treatment proximity allows us to determine the most relevant spatial scale at which hate crimes have an impact.

For further validation of our empirical approach, which assumes that voters living near hate crime locations are similar to those living somewhat further away, we examined voter demographics across multiple distance bins of 0.1 miles from the hate crime sites to deter-

mine the basic demographic composition of voters. Figure 3 illustrates the comparability of key demographic characteristics by distance. Our analyses include the race/ethnicity, gender, age, educational level, estimated income, and party affiliation of the individuals. Education is determined by whether a person holds a bachelor's or graduate degree (predicted by L2), and income is determined by whether it exceeds the median income for the area (also predicted by L2). We find that the demographic characteristics of those living very close to hate crimes and those living a little farther away are very similar. The consistency of the demographic patterns across nearly all distance bins further increases the credibility of our method of identifying hate crimes, in which hyperlocal variation is taken advantage of.[11]

Figure 3: Demographic Characteristics of Voters by Distance

Notes: These graphs illustrate the racial composition, gender, age, education, estimated income, and party affiliation of voters by distance. The x-axis represents the distance between the voter's residential address and the hate crime's location.

[11]The proportion of highly educated and high-income earners is approximately 80 percent, which is quite high and could be attributed to two factors. First, people with higher educational levels and higher income levels are generally more likely to participate in electoral politics. Secondly, those with lower levels of education or income may be disproportionately affected by missing data. It is important to note that individuals living within a close proximity to hate crimes and those living slightly further away also exhibit strikingly similar levels of education and income.

3.2 Estimating Specification

In light of our graphical evidence, we proceed to the main event study analysis and estimate the following:

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

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. $\sum_{j \neq -1} \text{Election}_j$ 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 further away (0.3 to 1.5 miles), relative to the same spatial comparison for white voters.

As before, we include voter fixed effects (φ_i) to control for individual characteristics that remain constant over time, and census tract-election fixed effects (λ_{ct}) to account for time-varying local socio-economic factors. 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 4 presents the baseline results from our event study specification. In the figure, there are three panels, each representing the impact on Hispanic, Black, and Asian American voters.

Panel A, which examines hate crimes against Hispanics, reveals a significant mobilization effect. After the occurrence of a hate crime, we observe a significant increase in voter turnout among Hispanic voters living nearby. The mobilization effect is strongest in the election immediately following the hate crime (i.e., period 0), with point estimates indicating an increase in turnout of approximately three percentage points. Despite diminishing over time, the effect remains positive and economically significant.

In panels B and C, we depict the effects of hate crimes against Black and Asian individuals, respectively. As for Black voters (Panel B), we do not observe any statistically significant changes in turnout following hate crimes. The point estimates remain near zero throughout the post-treatment period, with the confidence intervals consistently containing the zero. Despite the fact that Black individuals continue to be the most frequent targets of hate crimes, there is no significant response to anti-Black hate crimes within the Black community. Panel C also shows that hate crimes against Asian individuals do not significantly affect Asian American voter turnout. We note that our analysis includes only 31 anti-Asian hate crimes, most of which were committed after 2020. There are only a limited number of observations for the third election following the hate crimes, therefore there is a wide confidence interval. As an important point, all three panels indicate parallel trends with near-zero point estimates and statistically insignificant periods preceding the hate crime.

Panel A: Hate Crimes Against Hispanic

Panel B: Hate Crimes Against Black

Panel C: Hate Crimes Against Asian

Figure 4: Baseline Results: Event Study Plots

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

To summarize the results, we combined the first three years of dummies following each hate crime into a single post-crime dummy. Table 1 presents our baseline results and robustness checks for the impact of hate crimes on voter turnout by race and ethnicity. In column (1), the baseline estimate indicates that hate crimes against Hispanics lead to a 1.6 percentage point increase in voter turnout, which is equivalent to 3 percent of the mean and 17.0 percent of the racial turnout gap.

The effect is stable and significant across various robustness tests. First, we include hate crime event fixed effects in column 2 to account for the heterogeneity associated with hate

crimes. 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.[12] This helps account for the impact of crime in general on political responses. We use an alternative neighborhood definition, namely the zip code, and incorporate zip code-election fixed effects in column 4. Standard errors are also clustered at the zip code level. Los Angeles County has 290 zip code areas, compared to 2,344 census tracts. In column 5, we exclude voters who have been exposed to multiple hate crimes during the sample period in order to ensure our results are not driven by repeated exposure to discriminatory violence. Finally, to isolate changes within the electorate, we exclude movers in column 6 and newly registered voters in column 7. This ensures that our findings are not driven by shifts in the composition of the underlying electorate. Furthermore, we provide a detailed discussion in Appendix A on how hate crimes impact migration and voter registration. It does not appear that hate crimes influence the composition of the underlying electorate in a significant way.

The consistency of these results across different specifications in Table 1 provides further credibility to our main findings, indicating a robust mobilization effect among Hispanic voters in response to hate crimes. The results for Black and Asian American voters are presented in panels B and C, respectively. We conclude again that hate crimes do not significantly impact voting behavior in these communities: their magnitude is small economically and not statistically significant. In general, the mobilization effect observed among Hispanic voters is in contrast to the null results for Black and Asian American voters, which indicates that the impact of hate crimes on minority groups can differ considerably. In Section 5, we will examine the mechanisms that contribute to these differences.

[12]Data source: https://lasd.org/transparency/part1and2crimedata. Los Angeles County's administrative crime data lack information about the demographics of suspects and victims, which limits our ability to examine the effect of race-specific crimes on voter turnout.

Table 1: 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*** (0.005)	0.017*** (0.005)	0.020*** (0.005)	0.020*** (0.007)	0.014*** (0.005)	0.017*** (0.005)	0.016*** (0.005)
Obs.	17,494,480	17,494,480	17,494,817	17,606,052	15,817,686	17,218,384	16,011,254
Panel B: Black *Average Turnout Rate: 0.530*							
Average Treatment Effects	0.004 (0.004)	0.005 (0.004)	0.004 (0.004)	-0.003 (0.007)	0.005 (0.004)	0.004 (0.004)	0.004 (0.004)
Obs.	17,478,552	17,478,552	17,478,552	17,585,242	15,918,939	17,017,541	16,279,424
Panel C: Asian American *Average Turnout Rate: 0.530*							
Average Treatment Effects	0.001 (0.011)	0.001 (0.011)	0.001 (0.011)	0.001 (0.011)	0.007 (0.011)	0.001 (0.011)	-0.000 (0.011)
Obs.	2,621,583	2,621,583	2,621,583	2,638,018	2,478,792	2,553,006	2,360,072
Voter FEs	✓	✓	✓	✓	✓	✓	✓
Census Tract-Election FEs	✓	✓	✓		✓	✓	✓
Hate Crime Event FEs		✓					
# of Part I Crimes		✓					
Zipcode-Election FEs		✓					
Exclude		Multi-T	Movers	Regis.			

Notes: The table presents the results of estimating equation (2) 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 Heterogeneity Analysis

In this section, we examine the effects of anti-Hispanic hate crimes and how they vary based on voter and victim characteristics, as well as the location of the crime. By analyzing heterogeneity, we are able to determine which groups are more likely to respond to hate crimes, and which types of hate crimes elicit greater responses.

Panel A of Figure 5 examines the demographics of voters, demonstrating a generally consistent positive effect across various segments of the electorate. While female voters exhibit slightly stronger responses than male voters, and young voters show slightly stronger effects than older voters, these differences are not statistically significant at any conventional level. The consistency of this relationship suggests that hate crimes mobilize voters across a wide range of demographic characteristics. In particular, Democratic voters appear to show a stronger reaction to hate crimes than Republican voters, perhaps due to ideological differences. In light of the fact that Democratic ideology emphasizes diversity, inclusion, and social equality, Democratic voters may be more sensitive to hate crimes that target marginalized populations.

Panel B of Figure 5 examines heterogeneity across a variety of crime characteristics. The gender of the victim appears to have little effect on voter turnout, with similar effects being observed for both male and female victims. It is noteworthy, however, that the victim's age plays a significant moderating role. Hate crimes committed against older victims are more likely to elicit a strong reaction than hate crimes committed against younger victims (2.4 percentage points versus 0.8 percentage points). This could possibly be attributed to an increased perception of vulnerability among older residents of the community who are more integrated into their communities. Also, the location of the hate crime is an important consideration: incidents that occur in public spaces or businesses tend to increase turnout by 1.8 percentage points, whereas crimes occurring in residential areas exhibit a slightly lower mobilization effect with a broader confidence interval. It appears that hate crimes in public places may be perceived as more immediate threats to community safety, thus prompting a stronger response on the part of voters.

In general, these results indicate that, while anti-Hispanic hate crimes have a broad impact on all voters within the targeted group, certain subsets, such as Democratic voters, display a greater degree of responsiveness to them. Furthermore, hate crimes that occur in public

spaces or that affect more vulnerable victims tend to generate an increased level of attention from the local community.

Panel A: Heterogeneity Effects by Voter Demographics

Panel B: Heterogeneity Effects by Crime Characteristics

Figure 5: Heterogeneity Analysis

Notes: This figure presents the impact of hate crimes on Hispanic voters using stacked triple-differences estimates and 90% confidence intervals from equation (2). 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.

4.3 Spillover Effects of Hate Crimes on Non-targeted Groups

After examining the direct effects of hate crimes on targeted communities, we now investigate potential spillover effects on non-targeted groups. As demonstrated by Roman and

Thompson (2024), high-profile violence against LGBTQ+ individuals increases support for the LGBTQ+ community's rights and reduces negative attitudes toward LGBTQ+ individuals. These changes in prosocial attitudes, however, are short-lived. By conducting a complementary difference-in-differences analysis, we examine how different racial groups respond politically to hate crimes that target other communities. This spillover effect is crucial for interpreting our baseline findings and determining whether the observed political mobilization is a targeted response to victimized communities or a sign of broader shifts in political participation.

Figure 6 presents event study estimates examining how different racial groups respond to hate crimes targeting other groups. Based on panel A, White voters are not affected by hate crimes directed against minority groups in terms of their political participation. The estimated coefficients are precisely around zero with no discernible trend before or after hate crime incidents.

Similarly, there is limited evidence that cross-group spillovers are occurring among minority communities. Panel B illustrates that Hispanic turnout patterns remain stable after anti-Black or anti-Asian crimes. The results of panel C indicate that Black voter participation is not affected by anti-Hispanic and anti-Asian incidents. Panel D reveals no significant shifts in Asian voters' turnout following anti-Hispanic and anti-Black hate crimes.

The absence of significant spillover effects is consistent with the findings of Roman and Thompson (2024), which suggest that while hate crimes may have some spillover effects, these effects tend to be negligible. A pattern of targeted mobilization suggests that hate crimes result in highly specific political responses within the directly affected communities rather than any broader changes in the political participation.

Panel A: White Voters' Response

Panel B: Hispanic Voters' Response

Panel C: Black Voters' Response

Panel D: Asian American 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 American 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.

5 Mechanisms

Having established the baseline effects of hate crimes on voter turnout, particularly among Hispanic voters, we now turn our attention to understanding the underlying mechanisms. The varying political mobilization effects across different minority groups underscore the importance of uncovering these mechanisms to gain a deeper understanding of our findings.

5.1 Individual-Level Heterogeneity

To begin with, we examine whether the differential responses are due to systematic differences in voter characteristics. There is a possibility that Hispanic voters differ systematically from Black and Asian American voters in terms of socioeconomic status and political preferences, which might be a contributing factor to heterogeneous mobilization effects.

To test this hypothesis, we perform two separate matching analyses. We match Hispanic voters with Asian American voters and, separately, with Black voters based on key socioeconomic and political characteristics: education level (high school completion or higher), median income, party affiliation (Democratic), and age cohort (grouped into three-year intervals). To maximize statistical power, we allow up to eight Hispanic matches per Black or Asian American voter, with observations weighted by the inverse of match counts.

Figure 7 presents the event study estimates using these matched samples. In Panel A, Hispanic voters are matched with Asian American voters, while in Panel B, Hispanic voters are matched with Black voters. The mobilization effects observed among Hispanic voters in both cases closely mirror our baseline estimates, even after ensuring comparable individual characteristics. In light of this consistency across both matched samples, it is likely that differences in voter characteristics alone cannot account for the stronger political response among Hispanic voters.

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 and 90% confidence intervals using matched samples of Hispanic voters. Panel A shows results when Hispanic voters are matched to Asian American 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.

Since individual differences do not appear to contribute to heterogeneous responses, we turn our attention to contextual factors that may facilitate collective political action. Specifically, we investigate three mechanisms: community density and information dissemination through word-of-mouth, the role played by advocacy and service organizations in the community, and media coverage of the issue. These contextual factors may explain why similar individual characteristics may translate into different political responses for different racial groups.

5.2 Information Dissemination through Word of Mouth

Communities that are targeted often discuss hate crimes that occur in their local area, especially those that involve serious incidents. First, we propose that the majority of information regarding hate crimes is spread through word-of-mouth within Hispanic communities, which is highly correlated with Hispanic density. To test this hypothesis, we stratify our sample using data from the 2010 Census to determine the density of Hispanic populations in each census tract where a hate crime occurred. Specifically, we divide our sample into high and low Hispanic density areas based on the median (i.e., 45.1%).

The top panel of Figure 8 presents the results of this analysis. There is a non-trivial differ-

ence in the effect of hate crimes on voter turnout between areas with high and low Hispanic densities. Hispanic voter turnout increased by 1.9 percentage points in census tracts with higher Hispanic population density. The effect, on the other hand, is smaller and statistically insignificant in areas with a density of Hispanics below the median. This pattern suggests that population density and word of mouth likely play a crucial role in spreading information about hate crimes and mobilizing voters within the local community. Information is likely to spread more rapidly and widely through social networks in areas with a higher concentration of Hispanic residents, resulting in an enhanced political response.

Political mobilization effects differ across minority groups-characterized by significant responses among Hispanic voters, but a limited effect among Black and Asian Americans-need to be further investigated. In Appendix B, we provide a detailed description of the geographical patterns of hate crimes and residential distributions of different groups. We find that the majority of anti-Hispanic hate crimes occur in Hispanic-majority communities, while the majority of anti-Black and anti-Asian hate crimes occur outside of Black-majority and Asian-majority communities. Different locations of hate crimes and residential patterns may partly explain the lack of significant effects on Black and Asian American communities.

Figure 8: Potential Mechanism

Notes: This figure presents heterogeneous treatment effects estimated through stacked triple-differences specifications (equation 2), displaying point estimates and 90% confidence intervals of hate crimes' impact on Hispanic voter behavior across two key contextual dimensions: Hispanic population density and proximity to Hispanic advocacy organizations. The analysis is bifurcated into two panels: the upper panel examines differential effects across areas with high versus low Hispanic population density (above/below median), while the lower panel investigates heterogeneous impacts based on the median distance between hate crime locations and Hispanic advocacy and community service organizations. All regressions in our analysis incorporate voter fixed effects and census tract-election fixed effects. Standard errors are clustered at the census tract level.

5.3 Role of Local Advocacy Organizations

In social movements, large groups can exert significant political influence, but they must also face higher coordination costs when they organize collective action (Olson Jr, 1971; Tarrow, 1998). Despite the fact that group threats, such as hate crimes, can strengthen social pressure and strengthen group identity, thus reducing free-riders to some extent, we propose that local Hispanic advocacy and community service organizations play a crucial role in facilitating and coordinating collective action for Hispanics. They provide essential community services and have long-standing relationships, trust, and roots in the local communities they serve. A survey by Independent Sector (2024) reveals that 57% of respondents trust nonprofits, ranking them higher than government, business, and the media in terms of public trust. Because of their close ties to the community, local organizations are uniquely positioned to disseminate information and mobilize voters in response to hate crimes.

We examine this mechanism using data collected by Kim (2022) on Hispanic advocacy and community service organizations 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*. A total of 519 Hispanic organizations are identified in the dataset, 46 of which are located in the Los Angeles County. As part of our analysis, we conducted a subsample analysis by classifying our sample based on its proximity to Hispanic organizations in the local area. We categorize areas into "near" and "far" based on the median distance (i.e., 2.3 miles).

The bottom panel of Figure 8 presents the results. Following hate crimes in areas near Hispanic advocacy organizations, Hispanic voter turnout increases by 3 percentage points compared to their White counterparts. Conversely, areas further from such institutions show a smaller and statistically insignificant effect.

This finding emphasizes the importance of civil society infrastructure in mediating the relationship between discriminatory events and political behavior. While minority organizations are prevalent in American society and actively involved 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 local Hispanic organizations serve as crucial intermediaries during community crises such as hate crimes. They

play a key role in raising awareness about these incidents, organizing community responses, and facilitating get-out-the-vote efforts.[13]

5.4 Density-Organization Interaction

Prior analyses examined the impact of Hispanic population density and proximity to advocacy organizations separately, however these factors may be interconnected. The presence of advocacy organizations may also be more prevalent in areas with a higher concentration of Hispanic residents. To disentangle these effects and identify possible synergies, we partitioned our sample based on Hispanic population density as well as proximity to local organizations into four groups.

Figure 9: Mechanism Interaction

Notes: This figure presents heterogeneous treatment effects from stacked triple-differences specifications (equation 2), displaying point estimates and 90% confidence intervals of hate crimes' impact on Hispanic voter behavior, stratified by the interaction between Hispanic population density and proximity to Hispanic 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. Standard errors are clustered at the census tract level.

Figure 9 presents the estimated effects for each of these four subgroups. There is a clear

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

pattern in the results: the effect of hate crimes on Hispanic voter turnout is most pronounced in areas with high Hispanic population density and proximity to local organizations (β = 0.034). The magnitude of this effect is substantially greater than in areas that are characterized only by one of these characteristics. Last but not least, areas with both a low Hispanic density and a distance from local organizations demonstrate a small and insignificant effect.

These findings suggest that community structure and organizational resources complement each other in the facilitation of political mobilization in response to hate crimes. A dense Hispanic population contributes to information diffusion and community cohesion, while nearby advocacy organizations can provide the institutional support and resources required to convert community sentiment into concrete political action. The interaction effect may explain why some communities exhibit stronger political responses than others in the face of hate crimes. This study emphasizes the importance of both informal social networks and formal organizational structures in enhancing civic engagement in the wake of discriminatory violence.

Our results also speak to the broader literature on social capital and collective action (Olson Jr, 1971; Tarrow, 1998). A combination of dense social ties and formal organizational capacity can be particularly effective in overcoming the collective action problems inherent in political mobilization, particularly in the face of external threats. These results have significant implications for understanding the conditions under which minority communities can effectively counter discriminatory violence through democratic means.

5.5 Media Coverage

Despite the importance of word of mouth and local organizations in disseminating information about hate crimes, we also consider the role that media coverage may play in this process. 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.[14]

Based on our search, we identified 22 news articles related to hate crimes targeting minorities between 2014 and 2022. In total, twelve of the reports concern anti-Black hate crimes,

[14]We used the keywords "hate crime," "hate incident," and "hate" combined with specific ethnicities or races.

eight concern anti-Asian hate crimes, and two relate to White supremacy.[15] By utilizing details such as the date, location, and targeted group, approximately half of these reported incidents were successfully matched with our LACCHR hate crime data.[16] Only six of these matched incidents can be classified as Part I crimes, which are included in our main analysis. The rate at which our sample hate crimes are mentioned in local newspapers is very low, at approximately 1.25 percent, which suggests that media coverage is unlikely to be a primary mechanism for the dissemination of information about hate crimes in our study context.

6 Other Political Responses

6.1 Policy Preference

People's experiences of serious hate crimes within their communities may influence their political preferences and may serve as an important motivator to vote. For a better understanding of the political implications of hate crimes, we examine whether such crimes affect voters' policy preferences, particularly in relation to criminal justice and affirmative action.

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

First, we examine the impact of hate crimes on the policy preferences of voters regarding criminal justice reform as reflected in their voting decisions on Proposition 47 in 2014 and Proposition 57 in 2016. Both of these propositions sought to reduce penalties for certain non-violent offenses and reform the parole system. Based on voter support for both Proposition 47 and Proposition 57, we use the following difference-in-differences specification to examine how hate crimes influence voter support for these public policies. This analysis does not assume that support for the two initiatives measures the same thing. In other words, we do not assume that they would have the same level of support in the absence of the treatment.

$$Y_{bt} = \alpha \cdot \text{Post}_t + \sum_d \gamma_d \cdot \text{Dist}_{b(d)} + \sum_d \eta_d \cdot \text{Post}_t \cdot \text{Dist}_{b(d)} + \lambda_b + \epsilon_{bt} \tag{3}$$

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

[15] Additionally, there are 10 news reports on anti-Jewish hate crimes.

[16] Some news reports may lack the necessary details for matching, while others describe incidents suspected rather than confirmed as hate crimes.

geometric center of a census block to the location of the nearest anti-Hispanic hate crime that occurred between November 2014 and November 2016. Post_t is a dummy variable indicating year 2016.[17] 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.

Figure 10: Effects on Opposition to Sentencing Reform

Notes: This figure presents distance-based estimates and corresponding 90% confidence intervals of hate crimes on the share of "no" votes, estimated from Equation (3). The empirical analysis employs a comprehensive dataset of hate crime incidents occurring during the two-year period between November 2014 and November 2016. Standard errors are clustered at the census tract level.

The coefficients η_d in Figure 10 indicate a clear pattern: voters living near sites of hate crimes were more likely in 2014 to support the relaxation of the crackdown on crime in 2016, but in 2016 to oppose it. Within 0.1 miles of the hate crime, "No" votes increase by 3 percentage points. The influence of distance on this shift in policy preference diminishes as the distance from hate crime locations increases, but the effect on voter turnout is more extensive than the geographic impact. On face value, both the magnitude and geographical distance suggest that the observed changes in voting decisions can be explained not only by an increase in voter turnout, but also by shifting voting preferences.

The increased opposition to sentencing reform in hate crime-affected areas indicates that

[17]Due to the confidentiality of individual votes, we are unable to further break down voting preferences by racial or ethnic group. In spite of this, it is reasonable to assume that our approach reflects the policy preferences of Hispanic voters to some extent given that 48.0% of Los Angeles County's population is Hispanic.

these incidents have raised concerns about public safety and may result in a more punitive attitude. It could be interpreted as a defensive reaction, with voters seeking stronger law enforcement and stricter penalties in order to protect themselves from perceived threats.

6.1.2 Proposition 16 (2020)

Next, we analyze voters' preferences with regard to affirmative action policies. California's Proposition 209 prohibited the use of affirmative action based on race or gender in the public sector and for university admissions. Bleemer (2022) shows that Proposition 209 forced underrepresented minority freshman applicants to attend colleges with lower standards, which resulted in lower average wages later on in life, with Hispanic applicants being the most impacted.

The California Proposition 16 (2020) sought to repeal Proposition 209 and reinstate affirmative action in the public sector and in public university admissions. Given the positive impact that affirmative action has had on Hispanic students, we expect that Hispanic voters will be more inclined to support the Proposition 16, and this may be especially true for those who live in close proximity to anti-Hispanic hate crimes. Based on anti-Hispanic hate crime events occurring within one year of the vote for Proposition 16, we estimate the following equation:

$$Y_b = \sum_d \gamma_d \cdot \mathrm{Dist}_{b(d)} + \gamma X_b + \lambda_n + \epsilon_b \tag{4}$$

where Y_b represents support for affirmative action at the block level. The main independent variable of interest is $\mathrm{Dist}_{b(d)}$, which consists of exclusive treatment indicators that measure a block's distance to the hate crime. We also include a comprehensive list of census-block-level control variables, including population, male proportion, Hispanic proportion, and crime rates. We further include census tract fixed effects: λ_n, and cluster our standard errors at the census tract level.

Figure 11: Effects on Support for Affirmation Action

Notes: This figure presents estimates and corresponding 90% confidence intervals of hate crimes' spatial effects on the share of affirmative votes for Proposition 16, derived from equation (4). We construct the dataset using hate crime events that occurred within one year before Proposition 16. The standard errors are clustered at census tract level.

The results presented in Figure 11 demonstrate that there is an increase in support for affirmative action in areas adjacent to hate crimes. In proximity to hate crime locations, the share of "Yes" votes is higher, with the effect gradually decreasing with increasing distance. Increased support for affirmative action in areas affected by hate crimes may be the result of a greater awareness of racial and ethnic disparities, influenced by the experiences of individuals or communities who have been subjected to discriminatory violence. A growing awareness of these issues translates into concrete political action, with voters mobilizing to support policies that seek to address these systemic problems.

In Appendix C, we present a series of placebo tests designed to demonstrate that our results are not influenced by the characteristics of the community. Collectively, these findings provide important insights into the mechanisms that drive the increased voter turnout seen in our earlier analysis. Two policy demands appear to be related to the increase in political participation: improving community safety and promoting greater equality and opportunity.

6.2 Candidate Entry

There is a strong role played by descriptive representation in the formulation of policies (Chattopadhyay and Duflo, 2004; Beach and Jones, 2017; Fischer, 2023; Beach et al., 2024).

While Zonszein and Grossman (2024) finds that the number of hate crimes in constituencies with minority candidates narrowly winning versus narrowly losing increases by 67%, we pose the opposite question: may a serious hate crime result in more candidates from the targeted group running for office and more elected officials from that group?

The California Elections Data Archive (CEDA) provides comprehensive details on local elections in California. Information provided includes election dates, offices, candidate names, occupations, incumbent status, and vote shares. Our study focuses on Los Angeles County city council elections from 2004 to 2022. Over 5,000 candidates have run for city office positions during this period in 88 cities. Each city council election has an average of 2.5 White candidates, 2 Hispanic candidates, 1.1 Black candidates, and 1 Asian candidate. In addition, we combine these electoral data with hate crime data from the Los Angeles County Commission on Human Relations (LACCHR) covering the period from 2003 to 2022, which represents the most comprehensive dataset available to us.

We adopt a stacked triple-differences specification similar to the approach used by (Cengiz et al., 2019). In particular, we construct 12 different datasets, each of which corresponds to a different event year from 2008 to 2019. It includes treated cities that experienced serious hate crimes in year h but did not report any serious hate crimes in the four years preceding year h. The selection of a four-year period represents a compromise between the available sample period and local election cycles. Furthermore, we include clean control cities, which were unharmed by serious hate crimes during the four years prior to and after the event year h, resulting in an eight-year period. A city that does not meet these criteria is excluded from the dataset. 27 cities are designated as treated for anti-Hispanic hate crimes, 35 for anti-Black hate crimes, and 8 for anti-Asian hate crimes. In this manner, a robust comparison is made between affected cities and their control counterparts over the period of eight years. The following specification is estimated:

$$\begin{aligned} Y_{cgth} = {} & \alpha \cdot \text{Post}_t \cdot \text{Targeted}_g + \beta \cdot \text{Treated}_c \cdot \text{Targeted}_g + \delta \cdot \text{Post}_t \cdot \text{Treated}_c \\ & + \boxed{\theta \cdot \text{Post}_t \cdot \text{Treated}_c \cdot \text{Targeted}_g} + \lambda_{th} + \zeta_{ch} + \epsilon_{cgth} \end{aligned} \tag{5}$$

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}).

The results are presented in Table 2. In the aftermath of an anti-Hispanic hate crime, the number of Hispanic candidates running for city office rises by 0.695, which represents a 34.75% increase. However, the increase in Hispanic candidates does not translate into an increase in Hispanic officials. Furthermore, we do not observe an increase in the number of Black or Asian American candidates running for city office following anti-Black or anti-Asian hate crimes.

Table 2: 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 racially motivated hate crimes by participating in electoral politics. Using administrative data on hate crimes in Los Angeles County in conjunction with individual voter files and turnout records, we exploit hyperlocal variations in the location and timing of hate crimes. Our analysis indicates that anti-Hispanic hate crimes increase the turnout of nearby Hispanic voters by 1.6 percentage points. Furthermore, we demonstrate that hate crimes are associated with changes in policy preferences, particularly in terms of crime prevention and affirmative action. In addition, hate crimes motivate more Hispanic candidates to seek office in local government. It is interesting to note that we do not observe any similar shift in voting behavior among Black or Asian American voters following anti-Black or anti-Asian hate crimes.

In our paper, we discuss how public acts of discrimination and racism have ripple effects within minority communities – an issue that is both broader and deeper to our understanding of race and inequality. Besides the scope of this study, the broader impact of hate crimes on local communities is an important subject for future research. Regarding responses to hate crimes, this paper focuses primarily on formal electoral reactions, which likely represent only one aspect of broader community responses. While many individuals, particularly those without citizenship, cannot vote, they can still participate in community activities such as protests. As an example, numerous Asian communities in New York City protested anti-Asian hate crimes during the COVID-19 outbreak. Research in the future may be able to investigate these questions in greater depth by utilizing robust research designs and reliable data on hate crimes in order to develop a deeper understanding of their social consequences and community responses. It is also crucial to identify effective strategies for mitigating the adverse effects of hate crimes and for combating such incidents within local communities.

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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.

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Table A1: Robustness Checks: Alternative Ethnicity Predictions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Turnout (=1)					
	Hispanic		Black		Asian American	
Nearby*Post*Targeted Group	0.0159***	0.0151***	0.00221	0.00407	-0.00613	-0.00647
	(0.00406)	(0.00403)	(0.00385)	(0.00385)	(0.0106)	(0.0109)
Observations	22,368,060	22,591,168	18,138,397	17,868,506	3,053,726	3,024,287
R-squared	0.611	0.611	0.629	0.629	0.637	0.637
Prediction Method	BISG	fBISG	BISG	fBISG	BISG	fBISG

Notes: The table presents the main results using alternative race and ethnicity prediction algorithms: Bayesian Improved Surname Geocoding (BISG) (Imai and Khanna, 2016) and Fully Bayesian Improved Surname Geocoding (fBISG) (Imai, Olivella and Rosenman, 2022). Standard errors are clustered at the census tract level.

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A Migration Responses and Voter Registration

To interpret our main results, it's crucial to understand how hate crimes affect community composition through migration and voter registration. To do so, we conduct two complementary analyses. First, we analyze the impact of hate crimes on residential mobility patterns by examining address changes recorded in the voter file. Second, we analyze changes in the number of registered voters and first-time voter registrations following hate crime incidents.

A.1 Migration Responses

For each hate crime that occurred in year h, we construct two snapshots of voters residing within a 1.5-mile radius of the incident. The first snapshot, taken in year $h-3$, captures migration patterns prior to the hate crime, while the second snapshot, taken in year h, reflects migration following the incident. We then track whether these voters relocate outside their neighborhood, defined at the census tract level, over the subsequent two years—specifically, during years $h-2$ and $h-1$ for the first snapshot, and during years $h+1$ and $h+2$ for the second snapshot. We then estimate the following specification:

$$\begin{aligned}\text{Migrate}_{it} = \alpha \cdot \text{Targeted}_i + \beta \cdot \text{Nearby}_i + \delta \cdot \text{Post}_t \cdot \text{Targeted}_i \\ + \xi \cdot \text{Nearby}_i \cdot \text{Targeted}_i + \eta \cdot \text{Post}_t \cdot \text{Nearby}_i \\ + \boxed{\theta \cdot \text{Post}_t \cdot \text{Nearby}_i \cdot \text{Targeted}_i} + \lambda_{ct} + \epsilon_{it}\end{aligned} \tag{6}$$

where Migrate_{it} indicates whether voter i migrated out of the neighborhood 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 A2: Migration Responses to Hate Crime

VARIABLES	(1)	(2)	(3)
	Migration(=1)		
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 A2 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 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 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.

A.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:

$$
\begin{aligned}
Y_{bgt} = & \sum_{j \neq -1} \alpha_j \cdot \text{Year}_j + \theta \cdot \text{Targeted}_g + \gamma \cdot \text{Nearby}_b + \delta \cdot \text{Targeted}_g \cdot \text{Nearby}_i \\
& + \sum_{j \neq -1} \xi_j \cdot \text{Year}_j \cdot \text{Targeted}_g + \sum_{j \neq -1} \eta_j \cdot \text{Year}_j \cdot \text{Nearby}_b \\
& + \boxed{\sum_{j \neq -1} \beta_j \cdot \text{Year}_j \cdot \text{Targeted}_i \cdot \text{Nearby}_b} + \varphi_b + \zeta_{ct} + \epsilon_{bgt}
\end{aligned} \tag{7}
$$

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. $\sum_{j \neq -1} \text{Year}_j$ 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 A2. 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.

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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 A2: Effects of Hate Crimes on Voter Registration

Notes: This figure shows the effect of hate crimes on voter registration, along with a 90% confidence interval. 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. All regressions include census block fixed effects and census tract-year fixed effects. Standard errors are clustered at the census tract level.

B Explaining Heterogeneous Mobilization Effects

The variation in political mobilization effects across minority groups—characterized by significant responses among Hispanic voters but limited impact on Black and Asian American communities—warrants further investigation. We propose that group density could play a pivotal role in explaining these heterogeneous responses and highlight the geographical patterns of hate crimes alongside the residential distributions of different groups.

Figure A3 provides evidence for the community network mechanism 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 creates conditions conducive to rapid information dissemination through community networks, facilitating collective political responses.

In contrast, Panels B and C show different patterns for Black and Asian American 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.

Panel A: Hispanic Population Concentration

Panel B: Black Population Concentration

Panel C: Asian Population Concentration

Figure A3: 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.

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C Placebo Tests for Policy Preference

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 16, we perform a placebo test using crime events from the year following Proposition 16. The logic behind these tests is straightforward: if our identification strategy is valid, future hate crime events should not affect past voting behavior.

Figure A4: Placebo Test on Policy Preference

Panel A: Share of "No" votes

Panel B: Share of "Yes" votes

Notes: This placebo test examines policy preferences related to combating crime and affirmative action by separately estimating Equation 3 and Equation 4 using hate crime events that occurred after the propositions. Specifically, to ensure consistency, we construct the dataset using hate crime events within two years following Proposition 57 for combating crime and within one year following Proposition 16 for affirmative action. Panel A displays the effect of distance from hate crimes on Share of No votes for sentencing reform while Panel B presents its effects on Share of Yes votes for affirmation action. The standard errors are clustered at census tract level.

Panel A of Figure A4 presents the results of the placebo tests for opposition to sentencing reform (Propositions 47 and 57). It displays a distinct pattern compared to Figure 10. Unlike the clear decrease in effect over distance seen in Figure 10, 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 A4 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.

To further rule out the influence of neighborhood-specific characteristics, we use other propositions from the 2020 general election that are unlikely to be related to hate crimes as control policies for Proposition 16 (2020). Specifically, we include Proposition 19 and Proposition 24. Proposition 19 is tax-related, focusing on modifying tax assessment transfers and inheritance rules. Proposition 24 is business-related, aiming to expand the provisions of the Califor-

nia Consumer Privacy Act (CCPA) and establish the California Privacy Protection Agency to implement and enforce the CCPA. We estimate the following specification:

$$Y_{bp} = \alpha \cdot \text{Prop16}_p + \sum_d \gamma_d \cdot \text{Dist}_{b(d)} + \sum_d \eta_d \cdot \text{Prop16}_p \cdot \text{Dist}_{b(d)} + \lambda_b + \epsilon_{bp} \tag{8}$$

where Y_{bp} represents support for policy p at the block level. $\text{Dist}_{b(d)}$ consists of exclusive treatment indicators that measure a block's distance to the hate crime. Prop16_p is a dummy variable indicating Proposition 16. We further include census block fixed effects: λ_b, and cluster our standard errors at the census tract level.

Figure A5: Placebo Test on Policy Preference

Panel A: Share of "Yes" votes

Panel B: Share of "Yes" votes

Notes: This placebo test evaluates policy preferences related to affirmative action by estimating Equation 8 with alternative propositions serving as control policies. Panel A uses Proposition 19 (2020) as the control, while Panel B uses Proposition 24 (2020) as the control. The standard errors are clustered at census tract level.

The results are presented in Figure A5. Once again, we find that individuals residing closer to the locations of hate crimes are more likely to support affirmative action policies. 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.

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