Political Responses to Hate Crimes*

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Abstract: This paper investigates how targeted groups respond politically to hate crimes occurred in their local communities. We combine incident-level administrative data on hate crimes in Los Angeles County with L2 individual voter files, leveraging the hyperlocal variation in the location and timing of these incidents. Our findings reveal that serious anti-Latino/a hate crimes result in a 1.7 percentage point increase in voter turnout among nearby Hispanic voters compared to their White counterparts. We do not observe changes in registered voter composition or migration rates. Additionally, we show that hate crimes change voters' policy preferences on combating crime and affirmative action. Lastly, we find that more Latino/a candidates are running for city offices in cities that have experienced hate crimes. However, we do not find significant changes in political participation among Black and Asian communities following anti-Black and anti-Asian hate crimes, respectively.

Keywords: hate crimes, minority, mobilization effect, policy preference

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1 Introduction

Hate crimes are a global phenomenon that have persisted across diverse societies throughout modern history (Dancygier and Green, 2010). In recent years, their occurrence has alarmingly increased both globally and within the U.S. In 2022, the FBI reported 11,634 hate crimes in the U.S., a figure that continues to climb, with many incidents likely remaining unreported. As a form of "message crime," hate crimes can inflict harm beyond non-bias-motivated offenses (COGAN, 2002), potentially deterring civic engagement and undermining the foundations of democracy. However, these actions against specific groups can also provoke a backlash (Fouka, 2019), motivating individuals to unite and stand up for their rights. Despite the critical role of civic engagement in addressing these crimes (Farrell and Lockwood, 2023), our understanding of how targeted communities respond politically to local hate crimes remains limited, presenting a significant gap in both academic literature and policy formulation.

This paper examines the causal impact of hate crimes on political participation, specifically through changes in electoral turnout among targeted groups. The tension between mobilization and intimidation effects underscores the complexity of community responses to hate crimes and highlights the importance of empirical investigation into their impact on democratic participation. To disentangle the competing effects of mobilization and intimidation, our study employs a rigorous empirical strategy that addresses two key methodological challenges.

First, the incidence of hate crimes in a neighborhood often correlates with other socio-economic factors that independently influence political participation, such as non-bias-motivated crime rates. We overcome this by exploiting hyperlocal variations in the location and timing of hate crimes, comparing political participation among targeted groups and white voters before and after these incidents. Furthermore, recognizing that information about hate crimes typically spreads locally through word of mouth, we introduce an additional spatial dimension to our analysis. This involves comparing individuals living in close proximity to the incident site (within 0.5 miles) with those residing slightly farther away (0.5 to 2 miles) but still within the same neighborhood.

Second, the lack of reliable hate crime data poses a significant challenge. The FBI's

Uniform Crime Reporting (UCR) Program, a commonly-used source, suffers from severe under-reporting, with most agencies failing to report hate crimes, rendering it unsuitable for rigorous research (Kaplan, 2021). To overcome this limitation, we utilize a novel incident-level administrative dataset on hate crimes in Los Angeles County. This high-quality data is maintained by the Los Angeles County Commission on Human Relations (LACCHR),[1] which has collected hate crime reports since 1980 from diverse sources including law enforcement agencies, educational institutions, community organizations, and victims directly. Crucially, this dataset provides the exact location of each hate crime, enabling us to precisely measure exposure to these incidents. We integrate this data with the individual-level L2 voter file, encompassing all registered voters in Los Angeles County, allowing us to link hate crime exposure to individual voting behavior. To further address potential under-reporting issues, we focus on Part I offenses—serious crimes such as murder, aggravated assault, and robbery—which are more likely to be reported due to their severity.

Our results indicate that serious anti-Hispanic hate crimes lead to an increase in voter turnout among nearby Hispanic voters in subsequent general elections. This mobilization effect diminishes with distance and disappears beyond 0.5 miles. We show that individuals living very close to hate crimes (within 0.5 miles) are similar to those living slightly farther away (0.5-2 miles) in terms of basic demographic characteristics. We further present an event study plot and find that the mobilization effect is short-lived, with the largest impact observed in the following election. Overall, serious anti-Hispanic hate crimes increase the turnout of Hispanics in the surrounding areas by 1.7 percentage points (pp). These changes can be interpreted as shifts in individual electoral turnout following the hate crime, as our preferred specification controls for voter fixed effects and ZIP code-year fixed effects. Additionally, we do not observe changes in registered voter composition or migration rates.

Higher voter turnout among Hispanic voters may be associated with shifts in policy preferences. We further examine voters' policy preferences on combating crime and affirmative action. California Proposition 47 (2014) and Proposition 57 (2016) both aim to reduce penalties for certain offenses and decrease the prison population. We find that hate crimes occurring between 2014 and 2016 influenced voting behavior.

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

Specifically, a higher share of voters living near the site of a hate crime voted against Proposition 57 in 2016 compared to Proposition 47 in 2014. Furthermore, we find that a higher share of voters living near the site of a hate crime supported affirmative action, as indicated by voting against Proposition 16 in 2020. Lastly, we investigate the candidate entry decision. Our findings indicate an increase in the number of Latino/a candidates running for city office in cities that have experienced hate crimes. However, we do not detect significant changes in political participation within Black and Asian communities following anti-Black and anti-Asian hate crimes, respectively.

This article makes two main contributions. First, it documents the extensive political responses to hate crimes within local communities. The existing literature on hate crimes primarily focuses on studying the causes of hate sentiment/crime, with an emphasis on the significant role of mass and social media (Müller and Schwarz, 2020, 2023; Ang, 2023; Jiménez Durán, Müller and Schwarz, 2023), immigration (FOUKA and TABELLINI, 2022; Couttenier et al., 2024; Zonszein and Grossman, n.d.), and more recently, the impact of COVID-19 (Cao, Lindo and Zhong, 2023; Dipoppa, Grossman and Zonszein, 2023). Although hate crimes, as a form of message crime, can create significant externalities for local communities due to their targeted nature (Perry and Alvi, 2012; Stotzer and Sabagala, 2020; Jaskiewicz, 2023), there is little evidence on how local communities respond to hate crimes. We are the first to investigate communities' responses to hate crimes. Our findings indicate that Hispanic communities tend to respond to hate crimes by increasing political participation, whereas Black and Asian communities do not exhibit similar responses.

Secondly, this article adds to a burgeoning body of research illustrating the influence of violence on electoral participation. These strands of literature investigate how the presence of violence can shape an individual's involvement in the democratic process, including terrorist attacks (Berrebi, 2008; Gould and Klor, 2010; Montalvo, 2011; Hersh, 2013; Getmansky and Zeitzoff, 2014), mass and school shooting (Luca, Malhotra and Poliquin, 2020; Hassell, Holbein and Baldwin, 2020; Yousaf, 2021; Garcia-Montoya, Arjona and Lacombe, 2022; Marsh, 2023), police violence (Ang and Tebes, 2023; Morris and Shoub, 2024), and lynching (Jones, Troesken and Walsh, 2017; Williams, 2022). Mass and school shootings generally do not affect voter turnout rates at the county level, but they do influence voters' preferences on gun policy and an increase in Demo-

cratic party vote shares (Hassell, Holbein and Baldwin, 2020; Yousaf, 2021; Garcia-Montoya, Arjona and Lacombe, 2022). Violence against minority groups, such as the lynching of Black individuals in U.S. history, is found to discourage Black voter political participation both in the short term and over the long run (Jones, Troesken and Walsh, 2017; Williams, 2022). While police violence can lead to a 3%–5% increase in voter registration and vote counts, this effect is highly localized and is primarily observed within the census block where the violence occurred (Ang and Tebes, 2023). Our findings indicate that hate crimes, as a modern violent form of inter-group tension, mobilize Hispanic voters. This effect is not only greater in magnitude but also broader in geographic scope compared to the impact of police violence. Moreover, we find that the occurrence of hate crimes is associated with shifts in policy preferences.

2 Data and Hate Crimes in Los Angeles County

Our analysis focuses on Los Angeles County, the most populous and one of the most ethnically diverse counties in the United States. According to the 2020 census, Los Angeles County has over 10 million residents, with 48.0% identifying as Hispanic, 25.6% as White, 15.0% as Asian, and 7.9% as Black.[2] We primarily rely on two administrative datasets: an incident-level dataset on hate crimes from the Los Angeles County Commission on Human Relations (LACCHR) and an individual-level voter file from L2, which includes the universe of registered voters in the County of Los Angeles and their turnout records. We also supplement the analysis with data on additional political outcomes from other sources. Specifically, we obtain block-level vote share data for propositions from the Statewide Database and candidate data 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).[3] Established in 1944 following the "Zoot Suit Riots," LACCHR is an official agency dedicated to resolving intercultural conflicts and eliminating bias and prejudice in the richly diverse and multicultural County of Los Angeles.

[2]Source: https://data.census.gov
[3]https://hrc.lacounty.gov/

One of LACCHR's flagship initiatives is monitoring and tracking hate crimes. Since 1980, they have compiled data from over 100 law enforcement agencies, educational institutions, and community-based organizations. Each hate crime case undergoes a thorough review by LACCHR to ensure reporting consistency and accuracy.[4] LACCHR stands as one of the oldest and largest organizations of its kind, and it arguably maintains the highest quality of data on hate crimes in the United States: an extensive sample period, broad coverage of sources, consistent data classification methods, and a strong focus on ensuring accuracy in reporting.

The data includes all hate crimes reported to the LACCHR from 2014 to 2022, totaling approximately 5,500 incidents. This incident-level data provides detailed information on dates, exact locations, bias motivations, offense types, and the demographic profiles of both victims and suspects.[5]

Panel A of Figure A1 presents the time trend for all hate crimes documented in Los Angeles County. There has been an increasing trend in hate crimes, echoing the rising trend observed at the national level. Among these, 45.5% of hate crimes targeted Black, Latino, or Asian individuals, with 19.6% of those classified as Part I crimes, including murder (2.5%), robbery (8.1%), and aggravated assault (86.5%). In our analysis, we will primarily focus on Part I hate crimes due to their salience and the lower likelihood of under-reporting. Panel B of Figure A1 shows the time trend for all Part I hate crimes targeting Black, Latino, and Asian populations in Los Angeles County over the same period, which follows a similar pattern to that of all hate crimes.

Among these hate crimes, the Black community is the most targeted group, accounting for 62.3% of incidents. Anti-Latino/a biases are involved in 32.3% of cases, while 6.5% target the Asian community, with the majority occurring after the onset of COVID-19. 61.2% of suspects involved in anti-Black hate crimes are Hispanic, and similarly, 57.2% of suspects in anti-Latino hate crimes are Black. In the meantime, White individuals account for 28.8% of suspects involved in anti-Black hate crimes and 24.5%

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

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

of suspects involved in anti-Latino hate crimes.

Figure 1 illustrates the spatial distribution of hate crimes targeting Black, Hispanic, and Asian communities. Hate crimes occur across the entirety of Los Angeles County rather than being concentrated in specific neighborhoods, though certain areas do experience higher incidences than others. This variation may be closely correlated with area-specific characteristics, leading us to employ an identification strategy that leverages hyperlocal variations in the location and timing of hate crimes.

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



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

2.2 Data on Voter Turnout

Our analysis utilizes a comprehensive dataset from the California Historical Voter File (2014-2024), provided by a leading non-partisan voter data vendor L2.[6] This dataset provides a comprehensive snapshot of all registered voters in Los Angeles County (and California) from 2014 to 2024, with updates occurring approximately four times per year. The L2 Voter File contains a wealth of information, including each voter's complete turnout history for all general elections from 2008 to 2022, allowing us to track individual political participation over an extended period. Crucially, the dataset provides precise residential addresses for each voter, enabling us to conduct fine-grained hyperlocal analyses and accurately measure proximity to hate crime incidents. Additionally, it contains detailed information about individual voters, such as their gender, age, and (predicted) ethnicity, facilitating our examination of effects on targeted group and heterogeneity across various demographic groups.[7] To ensure our analysis accurately captures exposure to hate crimes, we construct a panel dataset by merging the annual L2 snapshot data from 2014 to 2024.[8] This approach allows us to match each hate crime's location to the voter's address in the corresponding year of its occurrence.

As of 2023, there were approximately 5.5 million registered voters in Los Angeles County. Among them, 41.8% are identified as Hispanic, 34.1% as White, 10.9% as Asian, and 6.6% as Black. There exists a significant turnout gap among these different demographic groups. In the 2020 presidential election, the turnout rates for Hispanic, White, Asian, and Black registered voters were 74.7%, 84.0%, 74.3%, and 78.7%, respectively. In addition to voter turnout, we use the L2 Voter File to analyze migration patterns and gain insights into voter registration trends.

2.3 Data on Policy Preference

In order to examine the impact of hate crime on voter preferences, we leverage voting data on three significant California propositions that addressed criminal jus-

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

[7] Since California doesn't mandate voters to self-report their race and ethnicity, L2 has developed a complex algorithm utilizing full names, census block data and known marriage indicators to predict race/ethnicity.

[8] For each year, we use the voter file updated in the first quarter; if that is not available, we use the second quarter's update.

tice reform and affirmative action. The first—Proposition 47 in 2014, also known as the "Safe Neighborhoods and Schools Act"—reclassified certain non-violent felonies as misdemeanors, specifically targeting drug possession and theft crimes under $950. This proposition aimed to reduce prison populations and redirect savings to crime prevention and support programs.

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

The third—Proposition 16 in 2020—sought to repeal Proposition 209, which was passed in 1996 and prohibited state governmental institutions from considering race, sex, color, ethnicity, or national origin in public employment, education, and contracting. Proposition 16 aimed to reinstate affirmative action in California's public sector.

Block-level estimates of the share of ballots cast for and against each proposition come from the California Statewide Database, providing granular data for analysis of voting patterns across different communities.[9]

2.4 Data on Candidate Entry

Data on candidates running for city elections in Los Angeles County is sourced from the California Elections Data Archive (CEDA).[10] CEDA is a dataset that contains detailed information on local elections in California, including election dates, offices, candidate names, occupations, incumbent status, and vote shares. Our focus is on city council elections in Los Angeles County from 2004 to 2022. The dataset includes data from 90 cities and covers over 5,000 candidates running for city office during the sample period. There is no available information on the candidates' race/ethnicity, so we predict race/ethnicity based on the full names using the R package *rethnicity*.[11]

[9] https://statewidedatabase.org/

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

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

3 Empirical Strategy

There is limited causal evidence regarding the impact of hate crimes on local communities. This is because analyzing the correlation between hate crimes and neighborhood outcomes is confounded by the fact that hate crimes tend to happen more frequently in disadvantaged areas with high rates of homicide and poverty. Therefore, if we regress local hate crime on voter turnout, it would likely be biased by geographic variations in political preferences and engagement. Even controlling for area fixed effects may not eliminate these biases, as shifts in law enforcement practices could also be linked to when and where hate crimes occur.

To address this, we exploit hyperlocal variation in exposure to hate crimes within neighborhoods similar to Ang (2021). In essence, identifying variation comes from comparing changes over time among voters residing very close to a hate crime with those living slightly further away but still in the same neighborhood. Therefore, both groups are likely to have similar backgrounds and experience comparable local conditions, except for the occurrence of the hate crime itself. Furthermore, as hate crimes typically target minority groups, we can compare minority group voters with white voters. By combining these two comparisons, we employ a triple differences stacked event study approach to estimate the causal impact of hate crimes on voter behavior within local communities. This method leverages the fact that most sampled hate crimes received minimal or no media coverage, leading any effects to be highly concentrated geographically. This creates significant treatment heterogeneity within neighborhoods.

3.1 Graphical Evidence

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

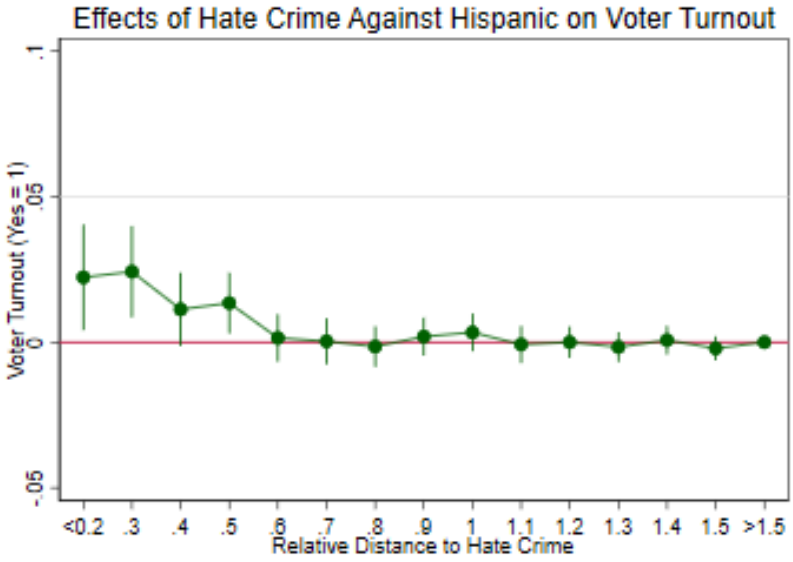
$$
\begin{aligned}
Y_{it} = \alpha \cdot \text{Post}_t + \beta \cdot \text{Targeted}_i + \sum_d \gamma_d \cdot \text{Dist}_{i(d)} + \delta \cdot \text{Post}_t \cdot \text{Targeted}_i \\
+ \sum_d \xi_d \cdot \text{Targeted}_i \cdot \text{Dist}_{i(d)} + \sum_d \eta_d \cdot \text{Post}_t \cdot \text{Dist}_{i(d)} \\
+ \boxed{\sum_d \theta_d \cdot \text{Post}_t \cdot \text{Targeted}_i \cdot \text{Dist}_{i(d)}} + \varphi_i + \lambda_{n,t} + \zeta_{c,t} + \epsilon_{i,t}
\end{aligned} \tag{1}
$$

where $Targeted_i$ indicates whether the voter belongs to the target group for the hate crime, $Post_t$ indicates whether the election in year t occurs after the hate crime, and Dist$i(d)$ represents a set of mutually exclusive treatment indicators that track a voter's distance to the hate crime. Of particular interest is the triple interaction term, $\sum_d \theta_d \cdot \text{Post}_t \cdot \text{Targeted}_i \cdot \text{Dist}_{i(d)}$, which captures the differential effect of hate crimes on the targeted group's turnout across different distance bands, relative to non-targeted groups and pre-hate crime periods. This specification allows us to trace out the spatial decay of hate crimes' impact with precision.

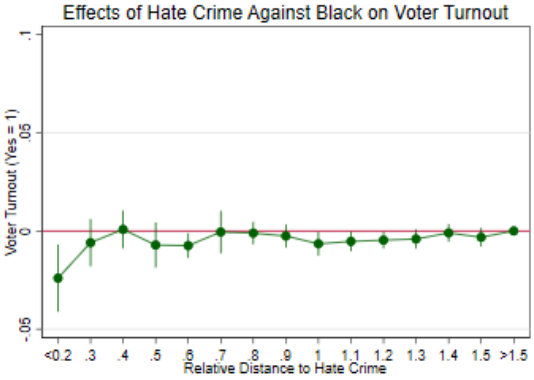
The comprehensive regression equation incorporates a robust set of fixed effects, including voter fixed effects φ_i, cohort-year fixed effects $\lambda_{n,t}$, and ZIP code-year fixed effects $\zeta_{c,t}$. Standard errors are clustered at ZIP code level.

For each hate crime, we focus on voters from the targeted group as well as white voters residing within a 2-mile radius of the incident, and we observe their turnout in the three general elections before and the three general elections after the hate crime.[12] For individuals who experienced multiple separate incidents (i.e., hate crimes occurring nearby on different days) during the sample period, we consider only the first incident. We estimate this model separately for anti-Hispanic, anti-Black, and anti-Asian hate crimes, producing a series of graphical representations that plot the estimated coefficients θ_d against distance in 2. These visualizations reveal nuanced patterns in the spatial reach of hate crimes' effects across different targeted groups. For Hispanic voters, we observe significant mobilization effects for those living nearby, which diminish with distance and disappear beyond 0.5 miles from the hate crime location, suggesting a relatively broad spatial impact. In contrast, the effects for Black and Asian voters appear more localized, with significant impacts concentrated within about 0.3 miles of

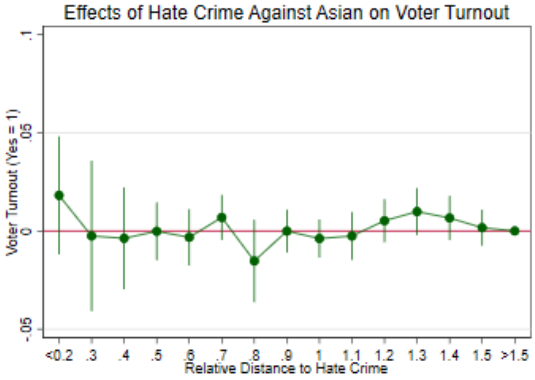
[12]Most state and local elections in California are on-cycle elections.



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 ZIP code-year fixed effects. Panel A displays the effect of distance from hate crimes against Hispanic individuals on voter turnout, while Panels B and C demonstrate the impact of hate crimes targeting Black and Asian voters. The standard errors are clustered at ZIP code level.

the incident.

These findings not only provide valuable insights into the spatial dynamics of hate crimes' political consequences but also inform our subsequent empirical strategy. Based on these results, we refine our definition of "nearby" treatment areas for our

main regression analyses, setting the threshold at 0.5 miles for Hispanic voters and 0.3 miles for Black and Asian voters. This data-driven approach to defining treatment proximity enhances the precision of our estimates and allows us to capture the most relevant spatial scale of hate crimes' effects for each targeted group.

To further validate our empirical approach and address potential concerns about the endogenous location of hate crimes, we present summary statistics in Table 1, which also serves as a balance test across our treatment and control groups. The table compares turnout and demographic characteristics of voters residing within and beyond our defined "nearby" thresholds (0.3 and 0.5 miles). Importantly, we observe no substantial differences in key demographic variables between these groups.

Our data shows that the fraction of Asian residents is 2.7% within 0.3 miles and 2.3% beyond, with a similar pattern for the 0.5-mile threshold. The Black population shows a slight difference, with 12.5% within 0.3 miles compared to 11.1% beyond, and 11.7% within 0.5 miles versus 11.1% beyond. Interestingly, the Hispanic fraction is slightly lower in the nearby areas (25.9% within 0.3 miles versus 27.4% beyond). Other characteristics such as the White population fraction (about 59% across all groups), gender ratio (approximately 50% male), average age (around 48-49 years), and political affiliation (Democratic party fraction of about 59-60%) show minimal variation across the distance bands. The largest difference is observed in the male fraction, which is 50.3% within 0.3 miles compared to 48.2% beyond, and 49.9% within 0.5 miles versus 48.1% beyond. Finally, the outcome turnout rate is slightly lower for residents living within 0.3 miles compared to those living 0.3 miles or more away, with a turnout rate of 0.551 versus 0.592, and this trend is similar for the 0.5-mile distance.

The balance across observable characteristics strengthens the causal interpretation of our subsequent identification strategy, as it indicates that our treatment and control groups are comparable in terms of pre-existing demographic and political factors. This mitigates concerns about potential upward bias in our estimates due to neighborhood composition effects.

Table 1: Summary Statistics

	(1) Full	(2) $\leq$0.3 miles	(3) $>$ 0.3 miles	(4) $\leq$0.5 miles	(5) $>$ 0.5 miles
Asian Frac.	0.023	0.027	0.023	0.026	0.023
	(0.150)	(0.163)	(0.150)	(0.160)	(0.150)
Black Frac.	0.111	0.125	0.111	0.117	0.111
	(0.315)	(0.330)	(0.314)	(0.321)	(0.314)
Hispanic Frac.	0.274	0.259	0.274	0.270	0.274
	(0.446)	(0.438)	(0.446)	(0.444)	(0.446)
White Frac.	0.592	0.588	0.592	0.587	0.592
	(0.492)	(0.492)	(0.492)	(0.492)	(0.492)
Male Frac.	0.483	0.503	0.482	0.499	0.481
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Age	49.380	48.356	49.407	48.460	49.450
	(17.610)	(17.240)	(17.621)	(17.290)	(17.630)
Democratic Frac.	0.599	0.590	0.599	0.595	0.599
	(0.490)	(0.492)	(0.490)	(0.491)	(0.490)
Turnout.	0.593	0.551	0.592	0.564	0.593
	(0.492)	(0.497)	(0.491)	(0.496)	(0.491)
Observations	37,774,198	981,740	36,792,458	2,718,234	35,055,964

Notes: This table presents summary statistics using L2 voter file data. For each hate crime incident, we retain voters residing within 2 miles of the crime location in the year of occurrence. We then merge each voter's turnout history for the election year, creating a panel dataset. This process is repeated for each hate crime, and the samples are pooled together. Column (1) shows descriptive statistics for the full sample. Columns (2) and (3) present subsample statistics divided by a 0.2-mile distance from the hate crime location, while columns (4) and (5) show subsample statistics divided by a 0.5-mile distance. Standard deviations are reported in parentheses.

3.2 Estimating Specification

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

$$\begin{aligned} Y_{it} = & \sum_{j \neq -1} \alpha_j \cdot \text{Election}_j + \beta \cdot \text{Targeted}_i + \gamma \cdot \text{Nearby}_i + \delta \cdot \text{Targeted}_i \cdot \text{Nearby}_i \\ & + \sum_{j \neq -1} \xi_j \cdot \text{Election}_j \cdot \text{Targeted}_i + \sum_{j \neq -1} \eta_j \cdot \text{Election}_j \cdot \text{Nearby}_i \\ & + \boxed{\sum_{j \neq -1} \theta_j \cdot \text{Election}_j \cdot \text{Targeted}_i \cdot \text{Nearby}_i} + \varphi_i + \lambda_{n,t} + \zeta_{c,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

Where Y_{kst} is the outcome of interest for voters k in ZIP code area n at election year t. The key parameter of interest is θ_j, which represents the triple-difference evnet study estimate of the effect in each election year relative to the hate crime occurrence. Specifically, θ_j captures the change in voter turnout for the targeted group residing within the defined "nearby" area (0.5 miles for Hispanic voters, 0.3 miles for Black and Asian voters) compared to those living slightly farther away (0.5 to 2 miles for Hispanic voters, 0.3 to 2 miles for Black and Asian voters), relative to the same spatial comparison for non-targeted (white) voters, and relative to the election immediately preceding the hate crime.

In the specification, we include a rich set of fixed effects and controls to account for various potential confounders. Voter fixed effects φ_i control for time-invariant individual characteristics, while ZIP code-election fixed effects $\lambda_{n,t}$ and cohort-election fixed effects $\zeta_{c,t}$ account for local time-varying factors and cohort-specific trends, respectively. Standard errors are clustered at the ZIP code level to account for error correlation over time within the 206 Hispanic, 271 Black, and 113 Asian samples' ZIP

codes.[13]

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

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 White Voters' Response to Hate Crimes

Before presenting our main results, it is crucial to address a potential concern regarding our empirical strategy. Our triple-difference specification relies on comparing targeted minority groups to white voters, who serve as a control group. However, this approach raises a valid question: Are white voters indeed a suitable control group, or do they also react to hate crimes in ways that could confound our interpretation of the estimated coefficients?

To address this concern and validate our empirical strategy, we conduct a preliminary analysis focusing solely on white voters. We construct a stacked dataset encompassing all hate crime events and estimate a difference-in-difference event study model using the entire sample of white voters. This specification includes a similar set of controls: voter fixed effects to account for time-invariant individual characteristics,

[13]The average population of each ZIP code area is 33,945 people with an average size of 16.11 square miles. These areas can vary in size from a few square miles to larger ones and may contain anywhere from a few dozen to several hundred census blocks.

ZIP code-by-election year fixed effects to control for local time-varying factors, cohort-by-election year fixed effects to capture cohort-specific trends, as well as indicators for treated distance and event year dummies - the key components of a difference-in-difference design.

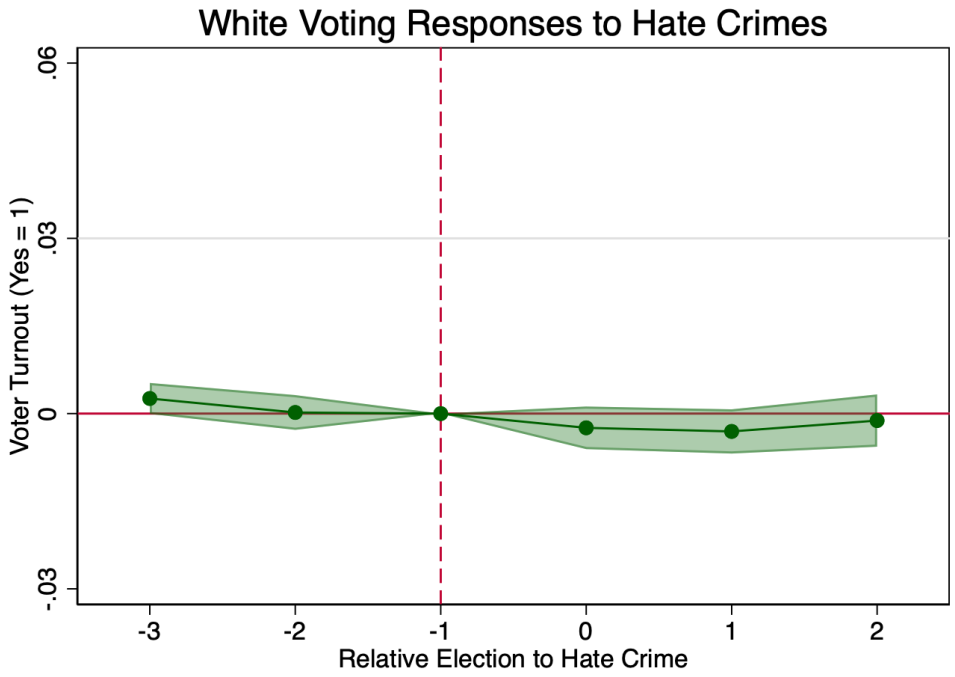


Figure 3: Validating the Control Group: White Voters' Response to Hate Crimes

Notes: This figure presents stacked difference-in-differences estimates and 90% confidence intervals for the effects of hate crimes on white voters, with standard errors clustered by ZIP code level. White voters are classified as "treated" if they reside within 0.50 miles of an anti-Hispanic hate crime, while control voters are those whose closest hate crime during the year falls between 0.50 and 2 miles away. In the case of anti-Black and anti-Asian hate crimes, being considered "treated" requires living less than 0.3 miles from the event. The standard errors are clustered at ZIP code level.

The results of this analysis, presented in Figure 3, are reassuring. The event study plot for white voters shows no discernible change in voter turnout across the event timeline. The estimated coefficients hover close to zero and exhibit no clear trend before or after the hate crime events. Moreover, the confidence intervals consistently include zero, indicating a lack of statistically significant effects at conventional levels.

This finding is crucial for two reasons. First, it suggests that white voters, on average, do not significantly alter their voting behavior in response to local hate crimes, regardless of the targeted group. This lack of response among white voters strengthens

their validity as a control group in our main analysis. Second, it alleviates concerns about potential spillover effects or general equilibrium responses that could complicate the interpretation of our triple-difference estimates.

The absence of a detectable effect on white voters' turnout does not imply their indifference to hate crimes but rather suggests that these events do not systematically alter their propensity to vote. This stability in white voter behavior provides a reliable baseline against which we can measure the responses of targeted minority groups.

Having established the appropriateness of white voters as a control group, we can proceed with greater confidence to our main findings, interpreting the estimated effects on targeted minority groups as reflective of their specific responses to hate crimes rather than general community-wide shifts in political engagement.

4.2 Voter Turnout

Figure 4 presents the baseline results from our stacked triple-differences event study, illustrating the heterogeneous effects of hate crimes on voter turnout across different targeted groups. The figure comprises three panels, each depicting the impact on Hispanic, Black, and Asian voters respectively.

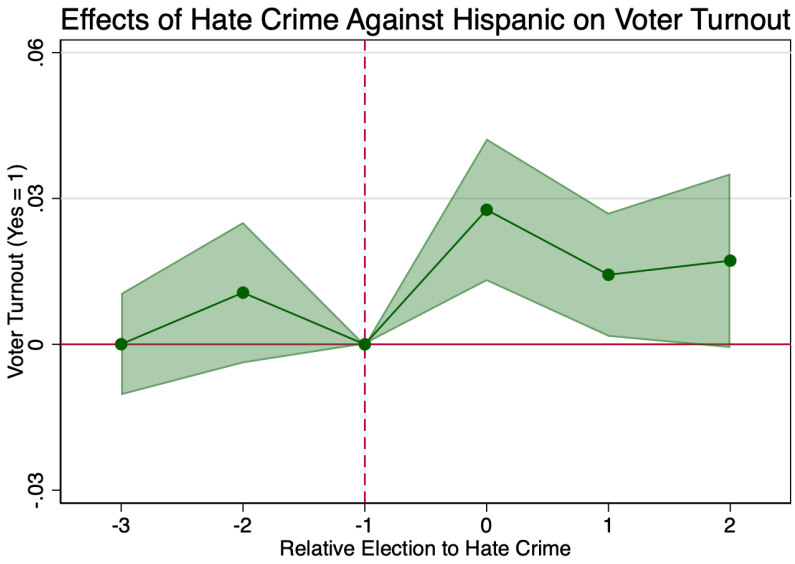
Panel A, which focuses on hate crimes against Hispanic individuals, reveals a notable mobilization effect. Following the occurrence of a hate crime, we observe a significant increase in voter turnout among Hispanic voters living within 0.5 miles of the incident location, relative to those living farther away and to white voters. This effect becomes apparent in the first election after the hate crime (period 0) and persists through subsequent elections. The magnitude of the effect is substantial, with point estimates suggesting an increase in turnout of approximately 3 pp in the election immediately following the hate crime. This persistent uptick in participation suggests that anti-Hispanic hate crimes may have a galvanizing effect on the Hispanic community's political engagement.

In contrast, Panels B and C, which illustrate the effects of hate crimes against Black and Asian individuals respectively, show different patterns. For Black voters (Panel B), we observe no statistically significant change in turnout following hate crimes. The point estimates hover close to zero across all post-treatment periods, with confidence

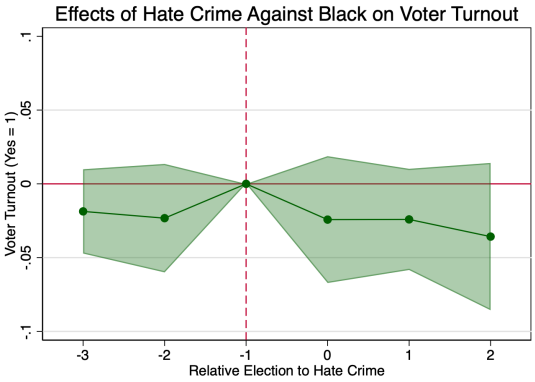
intervals consistently spanning the zero line. This lack of response suggests that anti-Black hate crimes do not significantly alter the voting behavior of the Black community, at least in terms of turnout. Similarly, Panel C indicates that hate crimes against Asian individuals do not lead to significant changes in Asian voter turnout. While there appears to be a slight positive trend in the point estimates for later post-treatment periods, these effects are not statistically distinguishable from zero, as evidenced by the wide confidence intervals.

Importantly, all three panels demonstrate flat pre-trends, with point estimates close to zero and statistically insignificant in the periods preceding the hate crime. This pattern supports the parallel trends assumption crucial to our difference-in-differences design.

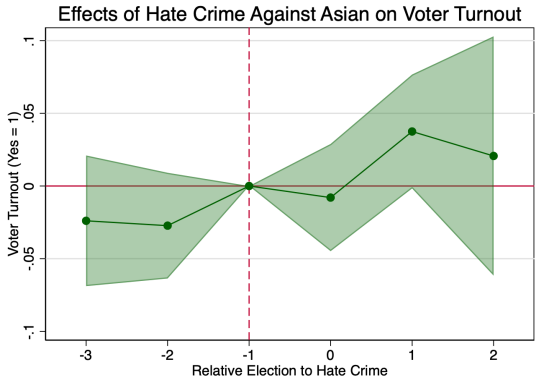
These results reveal a nuanced picture of how different communities respond politically to targeted violence. The mobilization effect observed among Hispanic voters contrasts sharply with the null findings for Black and Asian voters, suggesting that the political consequences of hate crimes may vary substantially across different minority groups.



Panel A: Hate Crimes Against Hispanic



Panel B: Hate Crimes Against Black



Panel C: Hate Crimes Against Asian

Figure 4: Stacked Triple Differences Event Studies: Baseline Results

Notes: This figure presents stacked triple-differences estimates and 90% confidence intervals for the effects of hate crimes based on equation (2), with standard errors clustered by ZIP code. Hispanic voters are considered treated if they live within 0.50 miles of a hate crime, while control voters are those whose nearest hate crime during the year was between 0.50 and 2 miles away. Black and Asian voters are treated at a distance of 0.3 miles. Panel A shows the impact of hate crimes against Hispanics, while Panels B and C show the impact on Black and Asian voters separately. The standard errors are clustered at ZIP code level in all regressions.

To summarize the results, we modified Equation (2) by combining the first three year dummies following each hate crime into a single post dummy. Table 2 presents our baseline results and various robustness checks for the impact of hate crimes on

voter turnout across different ethnic groups. The results reveal a nuanced pattern of responses across the targeted communities.

Panel A, focusing on Hispanic voters, demonstrates a consistent and statistically significant positive effect across all specifications. The baseline estimate in column (1) indicates that hate crimes against Hispanics lead to a 1.7 pp increase in voter turnout among Hispanic voters living within 0.5 miles of the incident, compared to those living farther away and to white voters. This effect remains remarkably stable and significant across various robustness checks, including the addition of crime event fixed effects (column 2), controlling for census block-level crimes (column 3), using more granular tract-year fixed effects (column 4), and excluding movers (column 5) or new registrants (column 6). The consistency of these results across different specifications strengthens the credibility of our findings, suggesting a robust mobilization effect for Hispanic voters in response to hate crimes.

In contrast, Panels B and C, which present results for Black and Asian voters respectively, show no statistically significant effects across most specifications. For Black voters, the estimates are consistently negative but not statistically distinguishable from zero. Asian voters show positive but statistically insignificant effects. These patterns for both Black and Asian voters persist across the various robustness checks, suggesting that hate crimes do not significantly alter voting behavior in these communities, at least in terms of turnout.

The robustness of these results across different specifications is noteworthy. The inclusion of crime event fixed effects, controls for block-level crimes, and the use of more granular geographic fixed effects do not substantially alter the estimates. Importantly, the results remain stable when excluding movers and new registrants, addressing potential concerns about selective migration or changes in voter composition driving the results. This consistency indicates that our findings are likely capturing genuine changes in political behavior among existing residents rather than compositional changes in the electorate.

In summary, these results provide robust evidence of a significant mobilization effect of hate crimes on Hispanic voter turnout, while suggesting no significant effects on Black or Asian voter turnout.

Table 2: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Turnout (=1)					
		Base			Alt. Controls	Alt. sample
Panel A: Hispanic *Average Turnout Rate: 0.516*						
Average Treatment Effects	0.017*** (0.006)	0.017*** (0.006)	0.017*** (0.006)	0.013** (0.006)	0.018*** (0.006)	0.017*** (0.006)
Panel B: Black *Average Turnout Rate: 0.548*						
Average Treatment Effects	-0.011 (0.008)	-0.010 (0.008)	-0.011 (0.008)	-0.000 (0.005)	-0.010 (0.008)	-0.011 (0.008)
Panel C: Asian *Average Turnout Rate: 0.523*						
Average Treatment Effects	0.010 (0.015)	0.010 (0.015)	0.010 (0.015)	0.006 (0.015)	0.009 (0.015)	0.007 (0.015)
Voter Fixed Effects	Y	Y	Y	Y	Y	Y
Cohort-Year Fixed Effects	Y	Y	Y	Y	Y	Y
Zipcode-Year Fixed Effects	Y	Y	Y	N	Y	Y
Crime Event Fixed Effects	N	Y	N	N	N	N
Type I Crime	N	N	Y	N	N	N
Tract-Year Fixed Effects	N	N	N	Y	N	N
Exclude	N	N	N	N	Movers	Regis.

Notes: The table presents the results of estimating equation (1) by replacing relative year indicators with a single post-treatment indicator. Treated distance refers to voters living within 0.50 (0.30) miles of a hate crime in the given year, while the control group consists of voters residing 0.5-2 miles away. The control group comprises White voters, and the treated groups are Hispanic (Panel A), Black (Panel B), and Asian Voters (Panel C). We conduct a triple-difference regression analysis, controlling for all relevant interaction terms across columns. We cluster standard errors at ZIP code level in all columns. Column (1) presents our baseline results, controlling for individual voter fixed effects, Cohort-Year Fixed Effects, and Zip code-election year FE. Column (2) adds hate crime event controls. Column (3) controls for Type I crime occurrence in the census block that year (affecting 9.7% of the sample). Column (4) replaces Zip code-election year FE with tract-election year FE. The sample size is different due to missing tract information for some voters. Column (5) excludes movers who relocated after the hate crime. Column (6) excludes new registrants who registered after the hate crime.

4.3 Migration Responses and Voter Registration

To address potential concerns about selective migration and changes in voter composition influencing our baseline results, we conduct two complementary analyses. First, we examine the impact of hate crimes on residential mobility patterns. Second, we investigate potential changes in the composition of registered voters and new voter registrations following hate crime incidents.

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

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

where $Migrate_{it}$ indicates whether voter i migrated out of the neighborhood (defined at the ZIP code level) in the two years following t. Nearby_i is a dummy variable that equals 1 if the voter resides in the nearby region (0.5 miles for Hispanic voters and 0.3 miles for Black and Asian voters). 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 ZIP code-year fixed effects, $\lambda_{n,t}$.

Table 3: Migration Responses to Hate Crime

VARIABLES	(1)	(2) Migration(=1)	(3)
Sample	Hispanic	Black	Asian
Nearby*Post*Targeted Group	-0.0103	0.00131	0.00465
	(0.00676)	(0.00939)	(0.0145)
Observations	11,800,420	11,684,895	2,055,449
Zipcode-Year FEs	Y	Y	Y

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 ZIP code 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 ZIP code-year fixed effects and cluster standard errors at ZIP code level in all regressions.

Table 3 presents the results of our migration analysis, examining whether hate crimes induce differential migration responses among targeted groups compared to non-targeted residents in the vicinity of these incidents. The results reveal no statistically significant effects on migration for any of the three targeted groups - Hispanic, Black, or Asian residents. For Hispanic residents, we observe a small negative coefficient (-0.010), suggesting a slight, albeit insignificant, decrease in the probability of moving following a hate crime. Conversely, for Black and Asian residents, the coefficients are positive but extremely small (0.001 and 0.005 respectively) and statistically indistinguishable from zero. These findings indicate that hate crimes do not substantially alter residential choices of targeted groups in the short to medium term.

To further investigate the impact of hate crimes on voter registration, we construct a dataset that includes all registered voters within a 2-mile radius of hate crime locations, covering four years before and four years after each incident. Specifically, we estimate the following specification to understand the compositional change in voter registration:

$$\text{Targeted}_{it} = \beta \cdot \text{Nearby}_i + \eta \cdot \text{Post}_t \cdot \text{Nearby}_i + \lambda_{n,t} + \epsilon_{it} \tag{4}$$

where Targeted_{it} equals 1 if the voter i belongs to the targeted group, and 0 if they are White. Nearby_i is a dummy variable that equals 1 if the voter resides in the nearby region (0.5 miles for Hispanic voters and 0.3 miles for Black and Asian voters). Post_t is a dummy variable indicating whether year t occurs after the hate crime. We control for ZIP code-year fixed effects, $\lambda_{n,t}$.

Table 4 examines the impact of hate crimes on the composition of registered voters (Panel A), new voter registrations (Panel B), and first-time voters (Panel C). Panel A shows no significant changes in the proportion of registered voters from targeted groups in areas near hate crime incidents. The coefficients for all three groups are small and statistically insignificant, suggesting that hate crimes do not lead to substantial changes in the overall composition of the registered voter population. In Panel B, we further examine the entry of new voters. Similarly, we find that the proportion of newly registered voters from the targeted group remains unchanged after the occurrence of hate crimes. Lastly, in Panel C, we focus on first-time voters, defined as those under the age of 23. First-time voters are of particular interest because they often have distinct political preferences compared to older cohorts. Moreover, the participation of first-time voters, especially from underrepresented groups, is crucial for fostering a more inclusive and representative democracy. We do not find that the occurrence of hate crimes in local communities affects the registration of first-time voters.

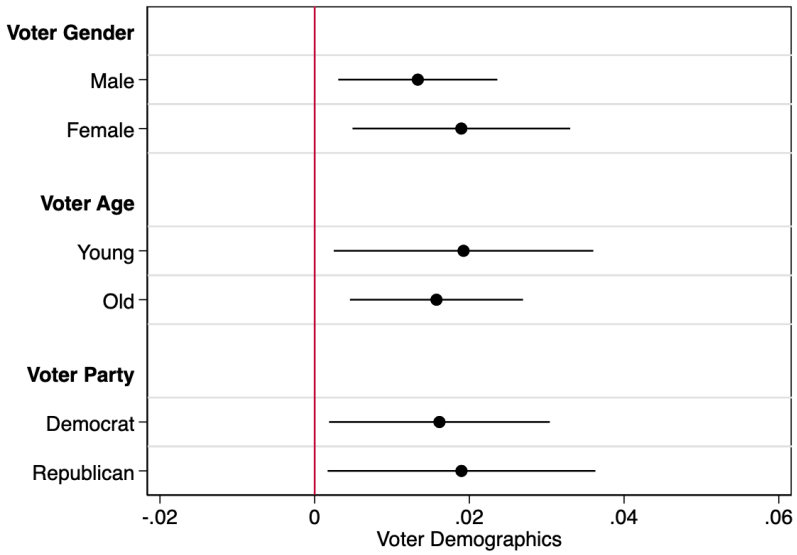
Taken together, these findings provide important context for interpreting our main results on voter turnout. The absence of significant migration responses and substantial changes in overall voter composition is reassuring for the internal validity of our turnout analysis. It suggests that the observed increase in Hispanic voter turnout is unlikely to be driven by compositional changes in the local electorate due to selective out-migration or differential registration patterns. Similarly, the null effects on turnout for Black and Asian voters cannot be attributed to differential migration or registration patterns.

Table 4: Composition Change of Voter

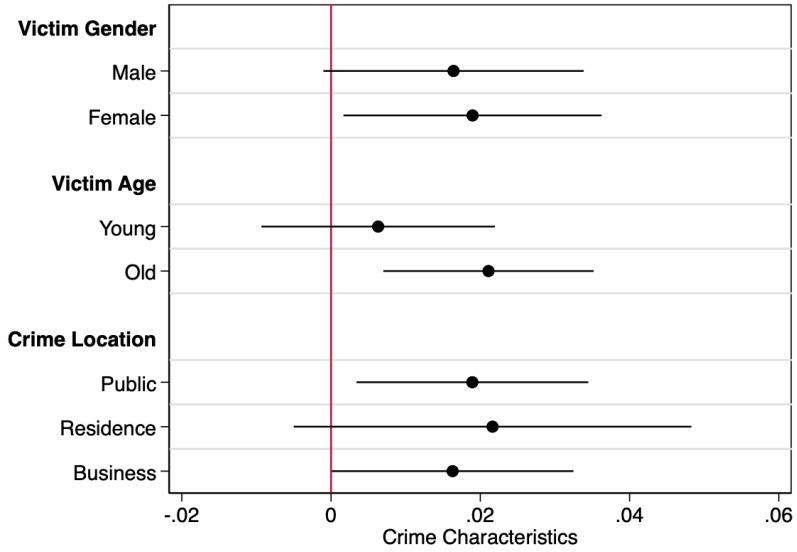
	Panel A: Registered Voter		
	Targeted Group(=1)		
Targeted Group	Hispanic	Black	Asian
Nearby * Post	-0.00101	0.00205	-0.00366
	(0.00156)	(0.00217)	(0.00354)
Observations	35,625,737	31,120,452	6,089,564
Zipcode-Year FEs	Y	Y	Y
	Panel B: New Registered Voter		
	Targeted Group(=1)		
Targeted Group	Hispanic	Black	Asian
Nearby * Post	-0.000384	0.00604	-0.00176
	(0.00416)	(0.00457)	(0.00615)
Observations	3,250,744	2,492,175	549,088
Zipcode-Year FEs	Y	Y	Y
	Panel C: First-Time Voter		
	Targeted Group(=1)		
Targeted Group	Hispanic	Black	Asian
Nearby * Post	-0.00463	0.00723	-0.0242
	(0.00498)	(0.00603)	(0.0162)
Observations	3,090,862	1,360,834	227,823
Zipcode-Year FEs	Y	Y	Y

Notes: This table shows the difference-in-differences estimates using the Hispanic (Column 1), Black (Column 2), and Asian (Column 3) sample, respectively. Outcome is defined as an indicator of whether someone is a target minority member. 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. We incorporate ZIP code-year fixed effects in all regressions. Panel A displays the effect using all registered voter, Panel B demonstrates the impact of hate crimes using new registered voters, and Panel C presents the impact of hate crimes using first-time voters. Standard errors are clustered are at ZIP code level.

4.4 Heterogeneous Analysis



Panel A: Heterogeneous Effects by Voter Demographics



Panel B: Heterogeneous Effects by Crime Characteristics

Figure 5: Stacked Triple Differences Event Studies: Heterogeneous Analysis

Notes: This figure presents heterogeneous stacked triple-differences estimates from equation (1) on the impact of hate crimes on Hispanic voters. All regressions in our analysis incorporate voter fixed effects, Zip code-year fixed effects, and cohort-year fixed effects. Panel A examines the heterogeneous impact across various voter demographics including gender, age, and party affiliation. In Panel B, we analyze the heterogeneous effects based on crime characteristics such as gender, age, and crime location (public places, residences, and businesses). The standard errors are clustered at ZIP code level.

The heterogeneous analysis presented in Figures 5 offers nuanced insights into how the effects of hate crimes on voter turnout vary across different voter and victim characteristics, as well as crime locations. This detailed examination uncovers important variations in political responses to hate crimes.

Panel A, focusing on voter demographics, shows generally consistent positive effects across different segments of the electorate. While female voters appear to have a slightly more pronounced response compared to male voters, and younger voters show a marginally stronger effect than older voters, these differences are not substantial. Similarly, both Democratic and Republican voters exhibit positive responses to hate crimes, with only minor differences between the two groups. This consistency suggests that the mobilizing effect of hate crimes on voter turnout may be relatively uniform across various demographic and political affiliations.

Turning to Panel B, which focuses on crime characteristics, we again observe relatively consistent effects across different subgroups. The gender of the victim appears to have little differential impact on voter turnout, with similar effects observed for both male and female victims. However, the age of the victim seems to play a more substantial role. Hate crimes against older individuals generate a stronger reaction compared to those against younger victims, possibly due to the perception of greater vulnerability among older community members who are more familiar within their neighborhoods. The location of the hate crime also emerges as an important factor. Crimes committed in residential areas show the strongest positive effect on voter turnout, followed by those in business locations, while crimes in public places have a comparatively smaller impact. This pattern suggests that hate crimes that intrude into people's immediate living and working spaces may be perceived as particularly threatening, leading to a stronger political response.

These heterogeneous effects provide valuable insights into the mechanisms through which hate crimes influence political behavior. They suggest that the impact of hate crimes on voter turnout is not uniform across all segments of society or all types of incidents. Instead, certain demographic groups - particularly women and young voters - appear more responsive to these events in terms of their political engagement to some extent. Similarly, the characteristics of the crime itself, especially its location and

the age of the victim, play a role in determining the strength of the political response. These findings have important implications for understanding community resilience and political mobilization in the face of discriminatory violence, and they underscore the complex interplay between social identity, perceived threat, and political action.

4.5 Discussion on News Coverage of Hate Crimes

In addition to the spread of hate crime news by word of mouth in local community, it can also be disseminated on a larger scale through local media outlets (Ang and Tebes, 2023). We conduct a search for hate crime-related news in the print editions of six local newspapers: the Los Angeles Times, the Los Angeles Daily News, Pasadena Star News, San Gabriel Valley Tribune, Torrance Daily Breeze, and Whittier Daily News.[14] Our search identifies 22 news articles related to hate crimes targeting minorities reported between 2014 and 2022. Of these, twelve are anti-Black hate crimes, eight are anti-Asian hate crimes, and the remaining two are related to White supremacy.[15] Some incidents are classified as possible hate crimes and are still under investigation. Ultimately, we are able to match half of these incidents to the hate crime data from the LACCHR based on details such as date, location, and targeted group. However, only six of these incidents are classified as Part I crimes, which are included in our analysis. Given the low rate at which sample hate crimes are mentioned in local newspapers (1.25%), it is unlikely that news coverage plays a significant role in disseminating information about hate crimes in our study context.

5 Other Political Responses

5.1 Policy Preference

5.1.1 Main Findings

To corroborate our earlier findings on increased voter turnout and provide a more nuanced understanding of the underlying motivations driving this heightened political engagement, we examine whether hate crimes influence policy preferences on criminal justice reform and affirmative action.

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

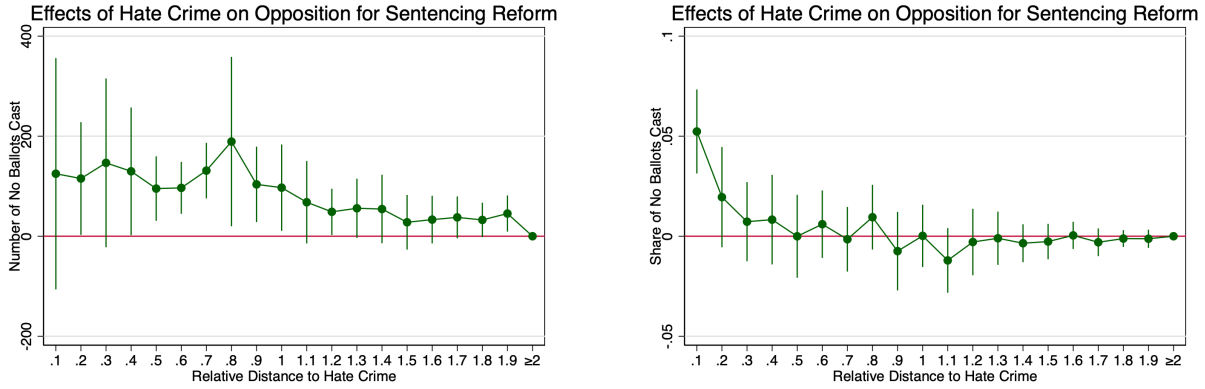
[15] Additionally, there are 10 news reports on anti-Jewish hate crimes.

First, we examine the effect of hate crimes on attitudes towards criminal justice reform, focusing on Proposition 47 in 2014 and Proposition 57 in 2016. These propositions aimed to reduce penalties for certain non-violent offenses and reform the parole system. To estimate the impact of hate crimes on voter support for these reforms, we employ the following difference-in-differences specification:

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

where $Y_{b,t}$ captures the number and share of "No" votes at the block level b. $\text{Dist}_{b(d)}$ represents a set of mutually exclusive treatment indicators that track a block's distance to the hate crime, whereas Post_t is a 2016 indicator. In the regression, we also control for census tract fixed effects λ_n. Standard errors are clustered by census tract level.

Figure 6: Effects on Opposition for Sentencing Reform



# of No Ballots Cast Share of No Ballots Cast

Notes: This figure reports stacked difference-in-differences estimates of the effects of hate crime based on equation (5). We construct the stacked dataset using hate crime events that occurred between 2014 and 2016, while also incorporating census tract fixed effects in our analysis. Panel A displays the effect of distance from hate crimes on number of No Ballots Cast while Panel B presents its effects on Share of No Ballots Cast. The standard errors are clustered at Census tract level.

The coefficients η_d in Figure 6 show a clear gradient, with stronger opposition in areas closer to hate crime locations, diminishing as distance increases. The proportion of "No" ballots cast increases closer to hate crime incidents, aligning with our previous findings on the hyperlocal nature of hate crimes' effects on voter turnout.

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

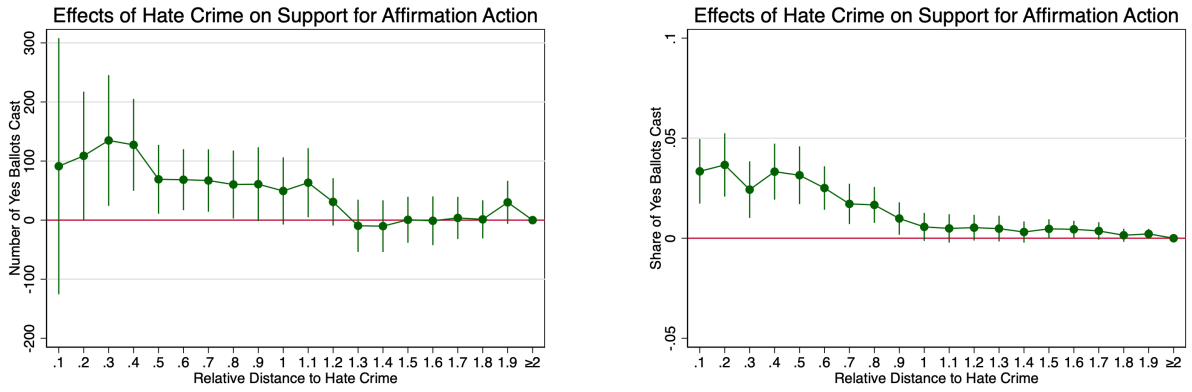
gests that these incidents heighten concerns about public safety and may lead to more punitive attitudes. This response could be interpreted as a defensive reaction, with voters seeking stronger law enforcement and stricter penalties as a means of protection against perceived threats. Such a shift in policy preferences is consistent with the increased voter turnout we observed earlier: voters are mobilizing not just to participate, but to advocate for specific policy positions they believe will enhance their security.

Next, we analyze support for affirmative action using data from the 2020 California Proposition 16, which sought to reinstate affirmative action in the state's public sector. For this analysis, we estimate the following equation:

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

Here, Y_b represents support for affirmative action at the block level. The main independent variable of interest is $\text{Dist}_{b(d)}$, which consists of exclusive treatment indicators that measure a block's distance to the hate crime. Similarly, we include census tract fixed effects denoted as λ_n and cluster our standard errors at the census tract level.

Figure 7: Effects on Support for Affirmation Action



# of Yes Ballots Cast Share of Yes Ballots Cast

Notes: This figure reports distance estimates of the effects of hate crime based on equation (6). We construct the stacked dataset using hate crime events that occurred between 2014 and 2020, while also incorporating census tract fixed effects in our analysis. Panel A displays the effect of distance from hate crimes on number of Yes Ballots Cast while Panel B presents its effects on Share of Yes Ballots Cast. The standard errors are clustered at Census tract level.

The results presented in Figure 7 show a marked increase in support for affirma-

tive action in areas closer to hate crime incidents. The share of "Yes" votes is higher in proximity to hate crime locations, with the effect gradually declining as distance increases.

This finding is particularly intriguing when juxtaposed with the results on sentencing reform. While voters in hate crime-affected areas show more punitive attitudes towards criminal justice, they simultaneously exhibit stronger support for policies aimed at addressing systemic inequalities. This seemingly paradoxical response suggests a nuanced reaction to hate crimes: a desire for immediate security coupled with recognition of the need for long-term societal changes to address underlying issues of discrimination and inequality.

The increased support for affirmative action in hate crime-affected areas may reflect a heightened awareness of racial and ethnic disparities, catalyzed by the personal or community experience of discriminatory violence. This awareness appears to translate into political action, with voters mobilizing to support policies they perceive as addressing these systemic issues.

These findings provide a richer understanding of the mechanisms driving the increased voter turnout observed in our earlier analysis. The surge in political participation appears to be motivated by dual, and not necessarily conflicting, desires: enhanced personal and community safety in the short term, and greater equality and opportunity in the long term. This multifaceted response underscores the complex ways in which hate crimes shape political attitudes and behavior.

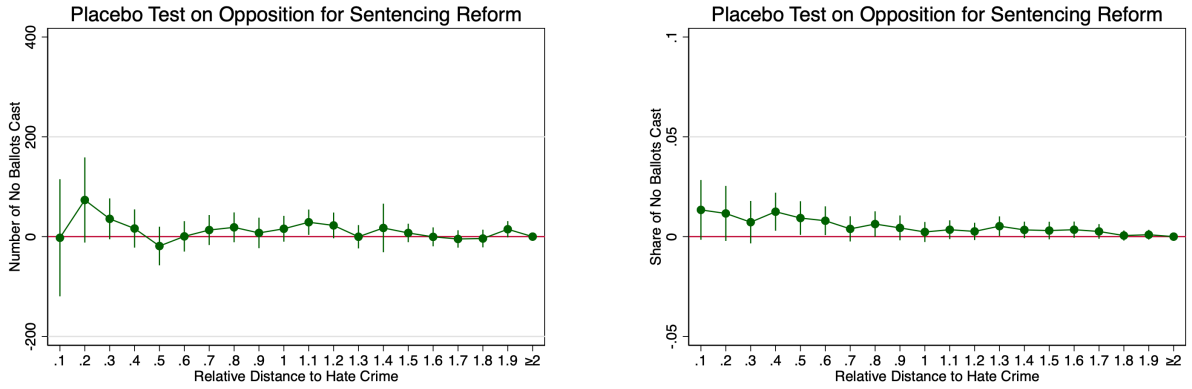
5.1.2 Placebo Test

To further strengthen the credibility of our findings on policy preferences, we conduct a series of placebo tests. These tests are designed to address potential concerns about the causal interpretation of our results and to rule out spurious correlations or unobserved confounding factors.

For our analysis of Propositions 47 and 57, which utilizes hate crime events from 2014-2016 in our original stacked dataset, we perform a placebo test using hate crime events from 2017-2022. Similarly, for Proposition 16, which originally used crime events from 2014-2020, we conduct a placebo test using crime events from 2021-2022.

The rationale behind these placebo tests is straightforward: future crime events should not influence past voting behavior if our identification strategy is valid.

Figure 8: Placebo Test on Opposition for Sentencing Reform

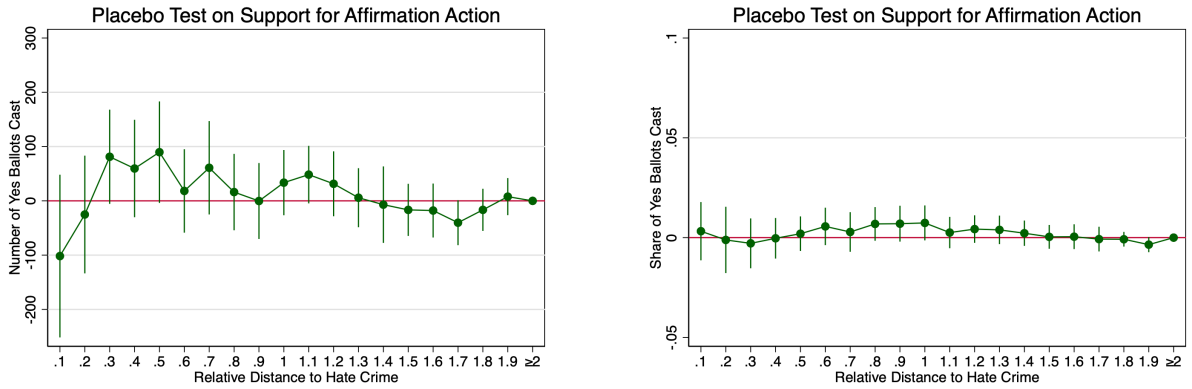


# of No Ballots Cast Share of No Ballots Cast

Notes: This figure reports stacked difference-in-differences estimates of the effects of hate crime based on equation (5). We construct the stacked dataset using hate crime events that occurred between 2017 and 2022, while also incorporating census tract fixed effects in our analysis. Panel A displays the effect of distance from hate crimes on number of No Ballots Cast while Panel B presents its effects on Share of No Ballots Cast. The standard errors are clustered at Census tract level.

Figure 8 present the results of the placebo tests for opposition to sentencing reform (Propositions 47 and 57). The result demonstrates a lack of significant effects across all distance bands from future hate crime locations. The point estimates hover around zero, with confidence intervals consistently overlapping the zero line. Similarly, Figure 9 illustrate the placebo test results for support for affirmative action (Proposition 16). Again, we observe no discernible pattern or statistically significant effects across different distance bands from future hate crime locations.

Figure 9: Placebo Test on Support for Affirmation Action



# of Yes Ballots Cast Share of Yes Ballots Cast

Notes: This figure reports distance estimates of the effects of hate crime based on equation (6). We construct the stacked dataset using hate crime events that occurred between 2021 and 2022, while also incorporating census tract fixed effects in our analysis. Panel A displays the effect of distance from hate crimes on number of Yes Ballots Cast while Panel B presents its effects on Share of Yes Ballots Cast. The standard errors are clustered at Census tract level.

The consistency of null results across both policy domains - sentencing reform and affirmative action - and across different outcome measures strengthens our confidence in the causal interpretation of our main results. Moreover, these placebo tests address potential concerns about reverse causality or anticipation effects. If areas more prone to hate crimes are also systematically different in their policy preferences for reasons unrelated to specific hate crime events, we would expect to see some effect in these placebo tests. The absence of such effects reinforces our interpretation that the policy preference shifts observed in our main analysis are responses to hate crime events rather than pre-existing differences in political attitudes.

5.2 Candidate Entry

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

officials from that group?

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

We adopt a stacked triple-differences specification similar to the approach used by (Cengiz et al., 2019). Specifically, we construct 12 distinct datasets, each corresponding to an event year from 2008 to 2019. Each dataset includes treated cities that experienced serious hate crimes in year h but reported no serious hate crimes in the four years prior to year h.[16] Additionally, we include clean control cities, defined as those that did not experience any serious hate crimes in the four years before and after the event year h, totaling an eight-year span. Cities that do not meet these criteria are excluded from dataset. This methodology ensures a robust comparison between affected cities and their control counterparts over the 8-years period. We estimate the following specification:

$$\begin{aligned} Y_{crth} = \alpha \cdot \text{Post}_t \cdot \text{Targeted}_r + \beta \cdot \text{Treated}_c \cdot \text{Targeted}_r + \delta \cdot \text{Post}_t \cdot \text{Treated}_c \\ + \boxed{\theta \cdot \text{Post}_t \cdot \text{Treated}_c \cdot \text{Targeted}_r} + \lambda_{t,h} + \zeta_{c,h} + \epsilon_{cth} \end{aligned} \tag{7}$$

where Y_{crth} is either the number of candidates from ethnicity group r running for city office in city c during year t or the number of elected officials from ethnicity group r running for city office in city c during year t. Treated_c is a dummy variable indicating

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

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_r equals 1 if the ethnicity group is the targeted group, and equals 0 for White. We control for election-year-event fixed effects ($\lambda_{t,h}$) and city-event fixed effects ($\zeta_{c,h}$).

Results are reported in Table 5. We find that, following a serious anti-Latino hate crime, the number of Hispanic candidates running for city office increases by 0.695, which represents a 34.75% rise in the number of Hispanic candidates. However, the increase in Hispanic candidates does not translate into a higher number of Hispanic officials. Moreover, we do not observe an increase in Black or Asian candidates running for city office following anti-Black or anti-Asian hate crimes, respectively.

Table 5: 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	X	.	X	.
City FEs	X	.	X	.
Election Year FEs	X	.	X	.
Event Year * Election Year FEs	.	X	.	X
Event Year * City FEs	.	X	.	X

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.

6 Conclusions and Future Directions

In this paper, we examine how targeted groups respond to hate crimes through electoral participation. By merging administrative data on hate crimes in Los Angeles County with individual voter files and turnout records, we leverage hyperlocal variations in the occurrence of hate crimes. Our analysis reveals that serious anti-Latino/a hate crimes result in a 1.7 percentage point increase in voter turnout among Hispanic voters compared to their White counterparts. We further demonstrate that hate crimes influence voters' policy preferences and lead to an increase in the number of Hispanic candidates running for local office. Notably, there is no similar shift observed in the behavior of Black or Asian voters following serious anti-Black or anti-Asian hate crimes, respectively.

Going beyond this paper, a crucial area for exploration is understanding the impact of hate crimes on local communities. The only existing study on this topic is by Jaskiewicz (2023), who uses UCR hate crime data and nationwide birth records to find that exposure to eleven or more anti-Black aggravated assaults during gestation in the residential county is associated with a decrease in birth weight of over 70 grams for Black infants. Many first-order outcomes of interest remain overlooked. For example, hate crimes can impact students' academic outcomes and mental health. Given that Black and Hispanic individuals are among the most frequently targeted groups, these potential consequences could further widen the achievement gap between minority and White students. Productivity is another critical dimension to consider, and we can further explore how hate crimes affect workers' productivity and their impact on the local firm. Future research should address these questions with careful research design and reliable data on hate crimes to gain a more comprehensive understanding of the social consequences of hate crimes. More importantly, we need further research to understand how to mitigate the adverse effects of hate crimes on local communities and how to combat hate crimes effectively.

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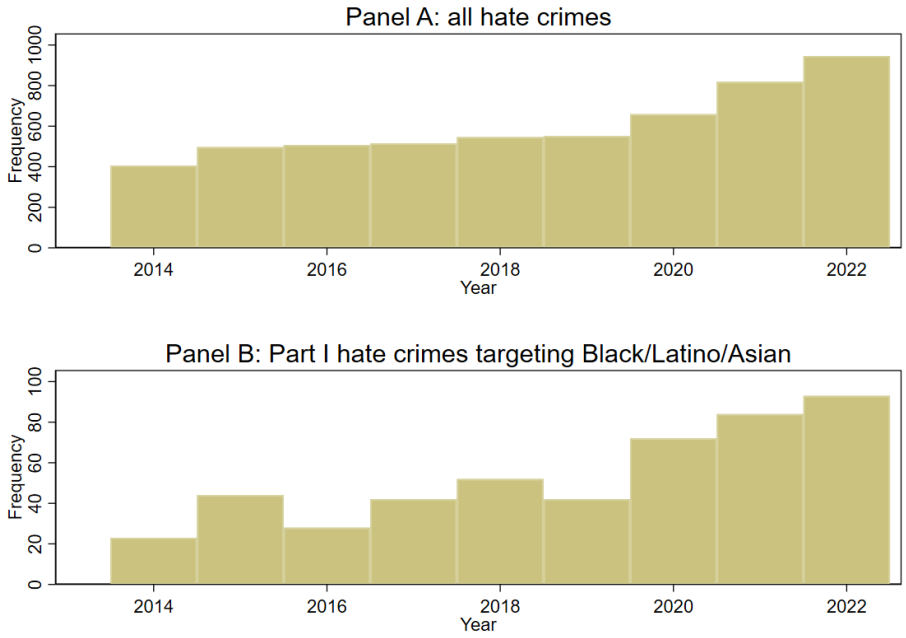
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Appendix

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



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