University of Antwerp
Faculty of Business and Economics

DEPARTMENT OF ECONOMICS

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Joel Carr

UNIVERSITY OF ANTWERP
Faculty of Business and Economics
City Campus
Prinsstraat 13, B.226
B-2000 Antwerp
Tel. +32 (0)3 265 40 32
www.uantwerpen.be

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University of Antwerp, City Campus, Prinsstraat 13, B-2000 Antwerp, Belgium
Research Administration – room B.226
phone: (32) 3 265 40 32
e-mail: joeri.nys@uantwerpen.be

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BLM Protests and Racial Hate Crime in the United States*

JOEL CARR
University of Antwerp

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Abstract

We provide evidence of the impact of protests following the death of George Floyd on anti-Black and anti-White hate crimes in the US. Using a regression discontinuity in time model, difference-in-differences, and synthetic control methods we find that recorded anti-Black (-White) hate crime increased by up to 15 (4) incidents per day or 259 (165) percent in June 2020. To account for changes in incentives to commit hate crimes during the coronavirus pandemic we control for other hate crime biases. We find that changes in unemployment due to the pandemic is a significant mediating factor in the hate crime shock against both groups and a larger shock in the first weeks of the protests in counties with a first BLM protest after Floyd's death. In addition, we test for mechanisms driving the changes, including retaliation, protectionism, and changes in victim reporting. Anti-Black hate crime is more sensitive to saliency of opposition to protests, "White genocide", and Derek Chauvin measured by tweets but less sensitive to cable news reporting. Using crime victimization survey we find that White hate crime victims were more likely to report victimization during the protests and evidence that police reduced effort toward Black hate crime victims and increased arrests of anti-White hate crime offenders. The results suggest that large scale protests or conflict between two groups during periods of increase in unemployment can lead to a substantial increase in expressed xenophobia.

JEL Classification: J15, K14, D74
Keywords: Racism; Hate crime; Crime

*Corresponding author: Joel Carr, University of Antwerp, Department of Economics; Prinsstraat 13, 2000 Antwerp, Belgium. E-mail: joel.carr@uantwerpen.be.

1 Introduction

Motivation — The public killing of George Floyd, a Black American, by Derek Chauvin, a White police officer, on 25 May 2020 sparked what would become the largest civil demonstrations in United States history. Led by Black Lives Matter (BLM) and repeating the words uttered in dying moments by multiple Black victims including George Floyd – "I can't breathe" – Americans across the country took to the streets in protest of what they viewed to be systemic racism perpetuated by the police forces of the country. Spurred on by the release of a 9-minute video recording of the murder the protests grew into the largest movement in United States history, surpassing even the Civil Rights era (Buchanan et al., 2020). At the peak of protests, support for the movement gained a majority across all races (Parker et al., 2020). Throughout late May and June, the protests as well as counter-protests increased in magnitude, leading to conflicts between BLM protesters, counter protesters, and law enforcement, culminating into a total of 25 confirmed deaths.[1]

Motivated by the historical size and persistence of the protests we analyze whether large anti-racism protests lead to an increase in racial hate crime against the conflicting groups – in this case Black and White Americans. Given the importance of social norms and social media we also ask whether the saliency of different topics on Twitter are correlated with observed changes in racial hate crime.

Following the Becker model of crime (Becker, 1968) we hypothesize that the 2020 Black Lives Matter protests affected hate crime by changing the perceived costs and benefits of committing a racial hate crime. These costs and benefits can be psychological, monetary, time allocation, social, and judicial punishment (Medoff, 1999). The perceived benefits of the crime will be determined by factors such as social norms and the individual's level of xenophobia and can include personal and social benefits (Hanes and Machin, 2014).

One possibility is that anti-Black hate crime increased as the (perceived) threat to potential offenders' preferred racial social structure grew. The triggering event — Floyd's death — and other recent killings such as Breonna Taylor could lead to retaliation against White Americans while Chauvin's arrest and perceived violence of the protests could lead to retaliation against Black Americans.

Costs include social costs of expressed racism, search costs, and expected punishment. Search costs for potential victims would be reduced during protests and perceived criminal justice costs reduced due to the conflict between protesters and

[1] https://www.theguardian.com/world/2020/oct/31/americans-killed-protests-political-unrest-acled

police. Both mechanisms would lead to an increase in racial hate crime.

Hate crimes are of great social concern as, compared to nonbiased crimes, they carry heavy costs on direct victims and the broader attacked group (distal victims). Relative to victims of similar nonbiased crimes, hate crime victims suffer more severe psychological effects such as level of intrusive thoughts, feelings of safety, nervousness, anxiety, withdrawal, and depression (McDevitt et al., 2001; Iganski and Lagou, 2015). Victims also modify behavior in order to avoid future attacks such as changing appearance and contact (Clark, 2014; Zempi and Chakraborti, 2015; Bachmann and Gooch, 2017). Moreover, hate crimes are more likely to involve "excessive violence", cause injury, lead to hospitalization, and involve multiple offenders, serial attacks, and repeat victimization of the same targets (Iganski, 2001).

Distal (indirect) victims of hate crime are affected similarly as direct victims, including family members and children (Williams and Tregidga, 2013; Zempi and Chakraborti, 2015). Being aware of violence directed toward someone of the in-group leads to similar emotional responses including anger, fear, inferiority, normativity of violence, as well as behavioral responses such as changing social interaction patterns (Walters, 2014; Paterson et al., 2019; Perry and Alvi, 2012). Indirect victims were also more likely to report avoidant and security-related behavioural intentions and hold negative attitudes towards government and certain criminal justice agencies but had strengthening effects on the community (Paterson et al., 2019).

Hate crimes against racial minorities not only can impact internal mobility but could reduce international mobility to the country with a reported hate crime shock. In the aftermath of the COVID pandemic and anti-Asian sentiment there is evidence that Chinese people are reluctant to travel to the United States and elsewhere abroad due to fear of victimisation.[2]

Literature — Research in economics on hate crime is largely concentrated in the effect of watershed or surprise events on racial or religious hate crime. This is due to the fact that hate crime data, compared to other crime data, is more limited and as such finding long-run relationships is difficult. Long-run changes and difference across locations in hate crime can in part be explained by changes in laws and reporting standards. Therefore, researchers look at temporary effects of shock events on hate crimes.

The most common type of event found in the literature is the positive short-run effect of jihadi terrorism on Islamophobic hate crime in the US or UK (Swahn et al.,

[2]https://morningconsult.com/2022/09/12/united-states-mass-shootings-violent-crime-deter-chinese-travelers/

2003; Deloughery et al., 2012; Hanes and Machin, 2014). Ivandić et al. (2019) investigate the effect of the Manchester bombing in 2017 and other domestic and foreign jihadi attacks on subsequent hate crime in Manchester and find a significant increase. Other researched terrorist events include September 11 (Swahn et al., 2003) and the 7/7 London tube bombings (Hanes and Machin, 2014).

More recently researchers have turned to unexpected political or electoral outcomes to identify causes of racial hate crimes. Hate crime in the United Kingdom temporarily increased after the vote to leave the European Union (Carr et al., 2020; Devine, 2021; Schilter, 2020; Piatkowska and Lantz, 2021; Williams et al., 2022). Romarri (2020) finds that elections of far-right mayors in Italy lead to increases in hate crimes in those municipalities. Hate crimes also increased following the election of Donald Trump (Edwards and Rushin, 2019; Levin and Grisham, 2016; Jenkins, 2017). This effect was strongest in counties with high twitter use, highlighting the mediating effect of (social) media (Müller and Schwarz, 2018). Müller and Schwarz (2020) also find that areas with higher anti-refugee sentiment on Facebook is correlated with higher crimes against refugees relative to comparable areas. Overall, access to the internet is found to increase hate crime, though the effect is largely found for "lonewolf" attacks and in areas with higher levels of racism (Chan et al., 2016).

Meanwhile, research in sociology and criminology suggests that as society progresses toward being more racially equal and inclusive there is a significant backlash among White Americans who feel they are now in a position vulnerable to discrimination (Isom Scott and Stevens Andersen, 2020). Perceived threats to the majority's power can result in identity crisis, attempts to control the minority population (Bobo and Hutchings, 1996), and violence against the "threatening" group (Isom Scott and Grosholz, 2019). Perceptions of White victimhood is usually connected to holding patriarchal gender beliefs (Isom et al., 2021), far-right political ideology (Boehme and Scott, 2020), and White supremacy (Berbrier, 2000).

Finally, research has shown the impact of exposure – positive or negative – on racial hate crimes. Positive exposure to Islam due to the prominent and open display of his religion by Mo Saleh of Liverpool FC led to a reduction in hate crime in Liverpool (Alrababa'h et al., 2021). Similarly, a hand gesture by ethnic-Albanian players referring to the Albanian Eagle led to a decrease in discrimination against Albanians in housing applications in Switzerland (Auer and Ruedin, 2022).

Contribution — We analyze the effect of race protests on hate crime victimisation of the protesting minority and majority groups. To this end we use a regression discontinuity in time, event study model, and synthetic control methods with hate crime against other groups as controls. In order to estimate the temporal effects we employ high-frequency data with information on victims' ethnicity or hate crime bias from the US obtained from the Federal Bureau of Investigation's (FBI) Uniform Crime Report.

Results show that recorded anti-Black hate crime (ABHC) increased immediately by 12-15 incidents per day. At its peak, ABHC increased by 259 percent in June 2020 and only returned to normal levels in December 2020. In comparison, anti-White hate crime (AWHC) increased immediately by 4-5 daily incidents or 165 percent in June. These results are robust to different specifications and placebo checks including permutation tests and placebo tests. There is no evidence of a substitution or spillover effects to other groups. Changes in racial hate crime are more sensitive to recent number of protests compared to the number of protesters. This demonstrates that the spread of the 2020 BLM protests created more of a shock to offenders and raised the threat of the protests.

Using costs of equivalent non-biased crimes from Chalfin (2015) we estimate that the additional recorded anti-Black and anti-White hate crime in the two months following the protests cost US society $37 million. Due to the dark figure of hate crime reporting (Pezzella et al., 2019) and higher psychological costs of hate crime this is likely to be a very conservative estimate. For example, the figure does not take into account the additional psychological costs to direct victims compared to non-biased crimes and the negative effects on distal victims of the targeted group.

Furthermore, we test mechanisms using a unique dataset of tweets pertaining to Black Lives Matter and the protests in the US. We use cable news headlines and Twitter data to analyse how the saliency of topics proxying mechanisms such as retaliation, protectionism, support and opposition correlate with changes in hate crime during the protests. Another contribution is the analysis of the relationship between online use of the n-word and racial hate crime.

We find that anti-Black hate crime is most (positively) sensitive to changes in the saliency of opposition to BLM and retaliation for the arrest or trial of Derek Chauvin. On the other hand, anti-White hate crime is negatively correlated with tweets on Chauvin and positively correlated with the general saliency of Black Lives Matter. ABHC and AWHC are not significantly correlated with changes in cable news headlines containing "Black Lives Matter". This suggests that either hate crime offenders or victims were more triggered by social media than traditional media, the latter being triggered into reporting victimization.

Looking at the effect of the protests by county characteristics we find that the largest difference is found in counties experiencing an above average increase in unemployment in 2020 from 2019. Meanwhile, areas with a larger 2020 vote share for Donald Trump and below average education levels experienced a larger increase in ABHC but smaller increase in AWHC. Finally, areas with higher income had a more significant treatment effect, particularly for ABHC.

The effect of the protests are first observed in counties holding the first racial justice protest or BLM protest in recent history. On the other hand, the stringency of state-level COVID policies did not play a mediating role, indicating that the mediating effect of the pandemic is through changes in economic conditions rather than a reaction to strict COVID policies such as lockdown.

In a final analysis we use the National Crime Victimization Survey (NCVS) to check for changes in reporting by victims and police response to racial hate crime victims. We find that the reporting probability increased significantly for AWHC with no corresponding changes in ABHC. Furthermore, there is evidence to suggest that police effort toward ABHC measured by response time and arrests decreased with weak evidence to the contrary for AWHC.

While we use BLM protests to research the effect of social movements on hate crime, the implications are not limited to racial hate crime and are relevant for social conflict regarding religion, sexuality, and gender. Given that economic and labor market conditions mediate the magnitude of the shock the results may not be unique to a global pandemic. Rather, any time of unemployment changes may agitate a hate crime contagion.

The remainder of the paper is as follows. Section 2 discusses the theoretical model and mechanisms, section 3 introduces the data while the empirical strategy is proposed in section 4. We continue to results in section 5, followed by mechanisms and then a conclusion.

2 Background

2.1 George Floyd and Black Lives Matter 2020 Protests

George Floyd died in Minneapolis, Minnesota on May 25, 2020. In response to his death the United States erupted into protest against police violence and racism as well as counter-protests. According to Count Love, in the height of the unrest there were over 200 daily protests with an estimated 200,000 daily protesters.

Opposition to the protests was greatest among older, Republican, and conservative men while support was correlated with the perception of local police exhibiting racial biases against Black Americans and in states with more fatal police shootings (Updegrove et al., 2020). Meanwhile, negative attitudes towards Black Lives Matter is strongly correlated with believing negative stereotypes (symbolic racism), equating the police to soldiers in war, and perceiving police misconduct to be less frequent (Ilchi and Frank, 2021). Favorability toward the police (perception of anti-Black discrimination) decreased (increased) sharply among low-prejudice and liberal Americans but remained unchanged among high-prejudice and conservative Americans (Reny and Newman, 2021). Similarly, research has found that reactions to the protests with respect to views of the police is mediated by pre-existing opinions about the racial composition of the protests (Dunbar and Hanink, 2022).

Research has also looked at the relationship between anti-racism protests and non-biased crimes due to concerns that large protests crowd-out police resources or a reduce police effort due to fears for their safety—the "Ferguson Effect" (Davenport, 2017). In the case of the latter, research has found no increase in deaths of police officers (Maguire et al., 2017). However, there is evidence of a significant decrease in killings by police, fewer property crimes, more murders, and lower property crime clearance rate (Campbell, 2021).

In response to the Ferguson protests police in Missouri conducted fewer stops and arrests but no significant effect on crime rates (Shjarback et al., 2017). There was also a decrease in traffic stops of White (16 percent) and Black (45 percent) drivers with no change in relative citation rates (Bolas, 2022). Finally, while decreases in policing can be explained by public scrutiny, evidence suggests the latter rather the former predicts best increases in crime (Capellan et al., 2020).

3 Data and Methodology

3.1 Data

Hate Crime

Hate crime in the United States is a traditional offence such as assault, vandalism, and robbery with an additional bias component. The Federal Bureau of Investigation (FBI) defines hate crime as "criminal offense[s] against a person or property motivated in whole or in part by an offender's bias against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity".[3] However, the FBI states that "hate itself is not a crime—and the FBI is mindful of protecting freedom of speech

[3]https://www.fbi.gov/investigate/civil-rights/hate-crimes#Definition

and other civil liberties."

The most salient hate crime includes mass murders such as the Pulse nightclub and Tree of Life synagogue shootings. However, a vast majority of hate crimes recorded by the FBI are relatively less serious offences such as assault (32.64%), vandalism (28.94%), and intimidation (26.43%).

One example of a hate crime prosecuted by the federal government is the June 6, 2020 verbal harassment (racial slurs, "Black lives don't matter") and assault with a bike lock of a Black teenager by a White adult in Michigan. While the verbal abuse is protected by free speech, the combination of the slurs and physical assault resulted in the event being treated as a racially-motivated hate crime.[4]

Hate crime data from the US is publicly available from the FBI's Uniform Crime Report. The original dataset contains information on the jurisdiction (area), date, motivation, and offender ethnicity. The motivation bias takes 33 different unique values which specify the (broad) ethnic group of racial hate crime and the religious group of faith-based motivations (see Table 1). We rearrange these motives into 6 biases: racial, religious, homophobic, transgender, gender, and disability and further disaggregate the racial and religious bias into 11 hate crime groups based on the specific group.

This data has been collapsed into a daily count of hate crime by the 11 racial and religious groups, disability, homophobic, gender, and transphobic hate crimes so that we have a panel data set with 15 hate crime categories.

The geographic distribution of recorded hate crime by US county is mapped for anti-Black and anti-White hate crime in Figures 1-2. The difference in levels by county are due to differences in population by ethnicity, state hate crime laws, and local hate crime recording practices by police as well as differences in true victimization (James J. Nolam et al., 2002; Grattet and Jenness, 2008; King et al., 2009). Monthly times series of the treated and control racial crimes, religious, homophobic, transphobic, and disability hate crime is shown in Figure 3.

Supplementary Data

Twitter data: Twitter data includes information on the saliency of All Lives Matter, Blue Lives Matter, police violence, defund the police, BLM protests, arrest and trial of Derek Chauvin, and white genocide. The list below provides some detail on how the saliency of different topics was measured using keyword searches on tweets during

[4]More examples of hate crimes from the Department of Justice: https://www.justice.gov/hatecrimes/hate-crimes-case-examples

the analysis period.[5]

1. All Lives Matter — “All lives matter” or “alllivesmatter”
2. Blue Lives Matter — “Blue lives matter” or “bluelivesmatter” or “Back the blue” or “backtheblue”
3. Defund the police — “Defund the police” or “defundthepolice”
4. BLM protests — BLM and protests
5. Police violence — “police violence” or “police brutality” or “excessive force”
6. Chauvin arrest — “Chauvin” and “arrest” or “trial”
7. White genocide — “White genocide”

Protest data: Protest data is available from Count Love[6]. Count Love gathers data on protests using local newspaper and television sites and manually codes information such as the date, location, size, and reason for the protests.[7] We include their data on protests under the category of “for racial justice”. This data is collapsed into a daily count of the number of protests as well as the sum of the estimated attendance of these protests.

Media: We also include in the analysis media data measured by television headlines of major cable news containing “Black Lives Matter” or “BLM” from archive.org. This supplements the twitter data as another source of news and proxies the saliency of the protests which may reach different demographics compared to social media. A time series can be found in Figure 13a comparing the daily count of BLM headlines of major cable news organisations and tweets. We find that the saliency of BLM increased immediately on twitter followed by cable news. Cable news coverage peaked in the second week of June and decreased over the coming months with the exception of Fox News, where coverage remained near peak levels through mid-July.

Google mobility: Google mobility compares mobility by category of locations to a baseline period is January 13-February 6, 2020. These categories include recreation/retail, parks, grocery/pharmacy, transit stations, workplaces, and residential areas. For the first five the measure captures the change in frequencies of visits from the baseline while the latter (residential) is measured in change of the duration.

[5] Additional information is available in the appendix or on request.
[6] countlove.org
[7] https://www.tommyleung.com/countLove/index.htm

Victimization Survey: Victimization survey data is available from the National Crime Victimization Survey (NCVS) for the years 1992-2021. The dataset contains information on crime victimization in the 12 months preceding the interview date. In addition to demographic variables such as race, individuals who self-report crime victimization are asked if the crime was motivated by a hate bias, reported to the police, the police response, and investigation outcomes. This allows us to estimate changes in the reporting probability of victims of racial hate crimes.

3.2 Methodology

To estimate the effect of the George Floyd protests on anti-Black and -White hate crime we use a regression discontinuity design, event study, and synthetic control methods. We include hate crimes against other groups to control for changes in expressed racism or other hate biases occurring during the pandemic and general social hardship during the concurrent COVID-19 pandemic.

Hate crime data is aggregated into 15 categories. This includes race by racial/ethnic group, religious hate crime by religion, homophobia, transphobia, disability, and gender hate crimes. In the end we have 12 control groups, with three other groups (anti-black, -White, and -multi racial[8]) as the treated units.

Regression Discontinuity in Time (RDiT)

We begin with a regression discontinuity in time (RDiT, henceforce RD) design to test if the onset of the protests immediately led to a change in racial hate crime. More specifically, an augmented local regression discontinuity is used to estimate the short-run shock to hate crime (Hausman and Rapson, 2018). If the shock on anti-Black and -White hate crimes was immediate we would expect to find a significant discontinuity at the beginning of the protests.

To perform an augmented local regression discontinuity difference-in-differences (difference-in-discontinuities) model we first regress the crime count on day-of-week dummies, month-of-year dummies, and a linear time trend, allowing all controls to differ by bias group using a fixed effects model. The residual of this regression is then used in a local model which estimates the discontinuity of the residuals at the time of the protests. The benefit of this method, compared to a local RD model, is that we can use the full sample period to remove long-term components of the data while focusing only on the days in the immediate vicinity of the cutoff (26 May 2020).

[8]Multi-racial hate crimes are excluded due to uncertainty of mechanisms but significantly increased following the protests. Results available on request.

Difference-in-Differences Event study

We next use a difference-in-differences event study design (ES) to estimate the temporal effects of the BLM protest on the treated hate crimes controlling for other hate crime biases. The model contains four pre-event periods and 14 post-event periods with 3 additional periods in early 2020. The latter periods and the choice of December 2019 as a baseline is motivated by the COVID-19 pandemic and possible changes in racial hate crime in this period (see Carr et al., 2022). Therefore our regression takes the following equation:

$$y_{at} = \sum_{t=-3}^{17} \alpha_t(I_t) + \sum_{t=-3}^{17} \beta_t(R_a \times I_t) + \psi_t + \theta_a + \varepsilon_{at} \tag{1}$$

Where y_{at} is deviation of recorded crime count against group *a* in day *t* relative to the pre-protest group average crime count. ψ_t and θ_a control for fixed month-of-year and day-of-week effects and crime effects, respectively. R_a is a treatment dummy variable equal to 1 for treated racial hate crimes. The coefficients of the pre-treatment dummy variables allow us to test the assumption of parallel trends. Significant pre-treatment effect are generally interpreted as evidence against the assumption. However, given the presence of COVID-19 and evidence of hate crime shocks against Chinese minorities (see Chelsea and Hansen, 2021; Carr et al., 2022; Lantz and Wenger, 2022) we hypothesize that hate crimes against some groups may deviate from expected levels. Therefore, with respect to the parallel trends assumption we are interested in the pre-treatment periods that do not contain the coronavirus pandemic.

Synthetic Control Methods

Due to concerns of the violation of the parallel trends assumption we next use synthetic control methods (SCM) (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2020). For this analysis we aggregate the data to a monthly count of hate crime by bias-type to ensure a smoother time series which facilitates a better match between the treated hate crime and its synthetic control (Abadie, 2020). Similar to the previous method, we standardize the count of hate crime by percent deviation from the pre-treatment group means.

The treatment effect is measured by the distance between the observed post-treatment outcome and the weighted basket of the 12 controls, that is:

$$\widehat{\beta}_{ct} = y_{ct}^1 - \sum_{c \in C} \omega_c y_{ct}^0, \tag{2}$$

where $\omega_c \geq 0$ is the weight attached to each bias c in the control group C. Since the treated group cannot be observed without treatment in the post-protest period the equation implicitly becomes:

$$\widehat{\beta}_t = \beta_t + \left(y_t^0 - \sum_{c \in C} \omega_c y_{ct}^0\right), \quad \text{for all } t \geq \tau. \tag{3}$$

The validity of this approach relies on minimising the difference in the parenthesis of Equation (3). We minimize the difference by matching only on the outcome variable itself as the crime groups are observed in the same locations. Therefore the matching weights are chosen to minimize the mean squared error of outcomes over the pre-protest period:

$$\frac{1}{t^0} \sum_{t<t^0} (y_t^1 - \sum_{c \in C} \omega_c^* y_{ct}^0)^2, \quad \text{for all } t^0 < \tau. \tag{4}$$

We match the standardized anti-Black and anti-White hate crime to the control basket–the 12 other hate crime groups–by minimising the predicted mean squared error of the four years prior to the protests. For this analysis the treatment begins in May 2020, of which only the last six days are truly treated.

Statistical significance or inference of the treatment effect in each post-protest month is determined by the likelihood of observing a greater treatment effect in a control hate crime relative to the pre-treatment mean squared prediction error (Abadie et al., 2010). Therefore, the treatment is significant at the 90% level if only one of the 12 controls experiences a greater "treatment" effect (positive or negative) in that month relative to the goodness-of-fit with its own synthetic control. This would implicitly test for a substitution effect as substitution would lead to a relatively large negative treatment effect for some of the control groups.

As robustness checks we follow the advice of Abadie et al. (2015) and remove the largest weighted group of the baseline results (homophobia). We also restrict the matching period to the three years prior to ensure that the results are not sensitive to the chosen matching period. Finally, we use changes in standard deviations as an outcome and perform a placebo-in-time test using May 2019 as the new treatment period, respectively.

4 Results

4.1 Baseline

Regression Discontinuity in Time

To first graphically demonstrate the short-run impact of the protests on racial hate crime, a regression discontinuity plot is shown in the top row of Figure 5. Here daily hate crime is condensed into bins in order to smooth the time series data and a line-of-best fit is estimated on each side of the treatment cutoff. Without controlling for other hate crime groups, the estimated jump in anti-Black and -White hate crime are 15 and 4 crimes per day, respectively.

Baseline RD results can be found in the second row of Figure 5. Using crime count as the outcome, we find a significant discontinuity in ABHC by 10-15 incidents per day. Daily hate crime against White Americans increased by 4-5 daily crimes. For both treated groups the estimated immediate shock to hate crime is stable across the three bandwidths (30, 40, and 50 days).

Event Study

Results for the baseline ES model can be found in Figure 6. The outcome variable is the relative crime count (deviation from pre-treatment average divided by average) and therefore the coefficients are interpreted as the percent deviation from the pre-treatment average.

We find that the treated hate crimes doubled in the week following the murder of George Floyd. In early June hate crime against both racial groups increased by over 300 percent. During the second half of 2020 daily hate crimes remained significantly elevated though the magnitude steadily decreased and became insignificant for ABHC in December 2020. Combining these effects we estimate that recorded ABHC increased by 1400 crimes in 2020.

Overall changes in the treated groups follow similar patterns. Only in one period–mid-June 2020–is there a significant difference in the shocks between the two groups. We also find no evidence of a violation of parallel trends for anti-Black hate crime. However, there is some concern of the validity of the assumption for anti-White hate crime as some of the pre-treatment coefficients are statistically significant. To verify the validity of both sets of results we next use synthetic control methods.

Synthetic Controls

Results for synthetic control methods are found in Figures 7-8 and Tables 2-3. The solid line of panels (a) show the actual relative hate crime level while the dashed lines represent the synthetic hate crime composed from the weighted control basket. The treatment effect is the vertical distance between the two while the validity of the results depends on a good overlap between the two prior to treatment. Panels (b) show the relative treatment effect of the treated group compared to the 12 control groups (placebo effects).

Anti-Black hate crime increased significantly in 2020 with the exception of October and December. In June, ABHC increased by nearly 260 percent compared to its synthetic counterfactual. Over time the treatment effect diminished and became insignificant in October. Moreover, the pre-treatment trends between actual and synthetic ABHC follow very similar patterns with no evidence that the two were diverging prior to treatment.

Compared to anti-Black hate crime the overlap between anti-White hate crime and its synthetic control is less close though still follows a similar pattern. This is due to the greater volatility of AWHC. Relative to the synthetic counterfactual AWHC increased in June by 165 percent and in July by 64 percent but was insignificant in August. Similar to anti-Black hate crime, there was a significant increase by 53 percent in November during the elections.

4.2 Robustness

RDiT

Results from the RD robustness checks can also be found in Figure 5. Each specification in the robustness section uses a 40-day bandwidth and (the residual of) crime count as the outcome with the exception of the logarithmic-transformed[9] outcome ("Log") and deviation from the crime average ("Relative"). For both ABHC and AWHC we find robust results when using a local linear or global linear model with inverse distance weighting as well as when using alternative measurements of crime as the outcome variable.

As a final robustness for our RDiT model we execute a permutation test by re-estimating the discontinuity at 1000 different points in time in the 6 years (2000 days) prior to the protests (Figure 9). The figure displays the histogram of the 1001 discontinuity parameters, including the real discontinuity. We find for both that less than 1 percent of permutations have a larger estimated discontinuity, further validating the baseline results. In most cases the estimated permutated jump is less than

[9]Logarithm of the count plus 1.

one-third of the actual discontinuity.

ES

Robustness checks for the event study model include restricted controls, alternative baseline period, and using monthly rather than daily data. Furthermore, to confirm the validity of the results we also change the composition of the control group and perform a placebo-in-time test using analogous dates in 2019, respectively. Results for the tests can be found in Figure 10 and support the baseline findings.

We also find no evidence of a substitution effect as there was no significant decrease in the control groups. There is, however, evidence of a spillover effect on other racial groups only in the week immediately following Floyd's death. This appears to be driven by a temporary increase in anti-Hispanic hate crime in the first week of protests.

SCM

Results for the robustness checks for synthetic control methods can be found in Figure 11-12 and corresponding Tables 4-11. The results for June and July are robust to different specifications including reducing the matching period to three years, removing homophobia from the control basket, and using changes from standard deviation as the measurement for crime. For the former two robustness we find similar treatment effects and statistical significance as the baseline. For the latter robustness check we find that ABHC increased by over 6 standard deviations in June and 3 in July. However, we no longer find significant effects in late summer 2020.

5 Mechanisms

5.1 Mechanisms Framework

The mechanisms guiding the effect of the murder of George Floyd on anti-Black and -White hate crime to be tested are motivated by research in hate crime typology (see McDevitt et al., 2002). These include:

1. Support or opposition (social norms) ($+$ or $-$) — The murder of George Floyd and subsequent protests may have increased the motivation to commit hate crime a hate crime by acting as an information shock regarding the acceptance of the expression of racial prejudice (Bursztyn et al., 2020). To test the correlation with expressions of support or opposition to the movement we use tweets contain-

ing keywords proxying these positions. For example, research has found that racially resentful individuals are more supportive of oppression by police (Metcalfe and Pickett, 2022) and therefore may respond positively to the saliency of violence by police against protesters (opposition).

2. Protectionism (+) — Protecting majority society. This includes protecting White society from racial homogeny or racial equity (Smith and King, 2021). As the protests become more salient the threat they pose to social power structure is perceived to be greater, increasing the benefits of anti-Black hate crime. Research finds that threat of harm is significantly correlated with perception of violence and support for repression toward the protests (Edwards and Arnon, 2021). Meanwhile, certain protest tactics increased fear which contributed to an increase in support for repression of the protests (Metcalfe and Pickett, 2022).

   According to the New York Times, nearly 40 percent of counties in the United States had a BLM protest in the month following Floyd's murder.[10] A vast majority of these counties had a White-majority population and on average had a population that was 75 percent White. This means that the BLM protests of 2020 were unique in that it elicited a large anti-racism response from White Americans. Compared to previous racial protests this would increase the risk to White society as the majority group is beginning to threaten perceived structural racism.

3. Retaliation (+) — Racial hate crime could increase due to retaliation similar to the reaction to terrorism (for example Hanes and Machin, 2014; Ivandić et al., 2019) and contentious trial verdicts (King and Sutton, 2013). We use tweets discussing the arrest and trial of Derek Chauvin to test for the effect of retaliation against the punishment of a police officer as well as retaliation against White Americans for the death of Floyd.

4. Economic hardship (+) — While we implicitly control for general effects of economic hardship using other ethnic groups as a control we can test if the effect of economic hardship mediated the effect of the protests on hate crime. Research has found evidence that unemployment or economic hardship is a catalyst to discrimination (Dustmann et al., 2011; Krosch and Amodio, 2014; Krosch et al., 2017) or hate crime shocks (Hovland and Sears, 1940; Hepworth and West, 1988; Falk et al., 2011; Bray et al., 2022). We test for an effect of economic hardship

[10] https://www.nytimes.com/interactive/2020/07/03/us/george-floyd-protests-crowd-size.html

using unemployment data by county and estimate the difference in effects between counties with above average (changes) in unemployment.

5. Mobility (+) — Mobility is likely to have been impacted by the concurrent coronavirus pandemic. We implicitly control for changes in mobility by using other hate crime groups or biases as controls. This accounts for all general effects of the coronavirus on racial hate crime. However, it is also possible that the mobility changes due to the protests themselves impact hate crime by increasing interaction between victims and offenders. Conversely protests could have an incapacitation effect as the protests gain in size due to the fact that this would mean large number of victims (safety in numbers) and police, increasing the expected probability of capture. To test the relationship between mobility and the hate crime shocks of the protests we use Google mobility data with six categories of mobility: retail/recreation, market/pharmacy, parks, transit stations, workplaces, and residential areas. This allows us to analyse in which type of locations the additional hate crimes were committed.

6. Reporting (+ or −) — An additional mechanism is reporting probability of hate crime victims. Salient events such as elections or protests could change the decision to report hate crime victimization to the police. Under-reporting has been found to be a particular concern for hate crime (Pezzella et al., 2019) and is related to perceptions of police legitimacy and lack of trust or confidence (Zaykowski, 2010; Myers and Lantz, 2020). Moreover, victims revealed that they did not report due to perceptions that the police *would not* do something rather than that they *could not* do something (Lantz and Wenger, 2020). This suggests that changes in the perceptions of police during the protests could impact reporting probability.

5.2 Mechanisms Methodology

Twitter, Protests, Mobility

To estimate the effect of these mechanisms we use a fixed effects panel approach where we include again our control hate crimes. We include the mechanisms of interest for the treatment period, allowing the effect of these variables to differ between the controls and treated hate crimes. The coefficient of interest is the interaction between the mechanisms and our treated group which captures the differential effect of the mechanism on the treated group. To measure the relationship with tweets and protests we use the (log-transformed) daily average in the past week of the mechanism variables to proxy recent exposure to these issues.

From the mechanisms in the framework we split the social norms into signals of opposition and support for the protests and exclude reporting and mobility which are tested separately. These four categories and their Twitter and protest measures include:

1. Opposition to Protests (+) — All lives matter, Blue lives matter, police violence against protesters

2. Support for Protests (−) — Defund the police, statues and monuments, number and size of protests

3. Protectionism (+) — White genocide

4. Retaliation (+) — Derek Chauvin's arrest

In a final use of twitter data we analyse the correlation between tweets containing the n-word and the treated racial hate crime. Next, we estimate the correlation between number of contemporaneous and recent protests and protesters. The correlation between the changes in mobility by location and treated hate crimes are estimated using a similar method as above.

Heterogeneity

We perform heterogeneity analysis to compare the effects of the protests by different crime and area characteristics using the event study model. These characteristics include region, population size of reporting agency, crimes against property or persons, offender race, presidential election outcomes, unemployment, wages, Black population, education, history of BLM protests, and state COVID-19 policies.

For region, crime type, and population size we aggregate the dataset by each of the categories. Regions split the United States into the census regions: West, North Central, South, and the Northeast. Crimes against person or property disaggregates the data based on if the target was property or a person. Population size refers to the size and classification (city or county) of the jurisdiction. We define the areas as being a very large city (>1 million), large city (100,000 - 1 million), medium city (10,000-100,000), small city or county, and medium/large counties. The effect of the protests are estimated separately by category.

The next heterogeneity analysis uses results of the 2016 and 2020 presidential elections by county which is then matched to the county of the hate crime. The data is then aggregated by counties won either by the Democrat or Republican candidate. In addition, we check how changes between the 2016 and 2020 elections correlate with hate crime shocks by separating the dataset between counties with an increase in vote share for Donald Trump in 2020 and those with a decrease.

Other county characteristics include changes in unemployment between 2019 and 2020, income, education levels, and racial composition. In the case of the county demographics, the data is disaggregated by areas with above and below the national average. These two subsamples are estimated together with the coefficient of interest capturing the difference in the treatment effect between the two groups (effect on above average areas minus below average areas).

A comparison between states with high and low levels of stringent COVID policies and economic support by state governments during the pandemic prior to the protests is performed to analyze the mediating effect of COVID-19. The final heterogeneity by characteristic analyses separately the impact of the protests between counties that had a BLM protest prior to Floyd's death, counties with their first BLM protest after May 26, and counties with no recorded BLM protest.

Next, the effects of the protests following George Floyd's death are compared in magnitude to other salient police-related deaths of Black Americans. To this end we use an augmented regression discontinuity with the cutoff the day after each death (see notes of Figure 20 for list of deaths and dates). For deaths occurring within a few days of each other the discontinuity is estimated once using the day following the first death. Also included is a daily time series for tweets containing "Black Lives Matter" to demonstrate online response to the deaths.

Our final mechanism to analyze is the effect of victim reporting probability on observed hate crime increases. Any estimated increase in crime data may simply be due to changes in victim behavior rather than changes in the frequency of victimization. To ensure that the results found in the previous sections are not due to an increase in reporting by the victims we use the National Crime Victimization Survey (NCVS).

We restrict the sample to respondents who are Black or White and self-report racial hate crime victimization and test if the probability of reporting changed following the protests, i.e. a difference estimator. We also test if reporting of all crime victimization types changed to see if the protests had broad effects on the reporting probability of crimes.

The victimisation survey is used to test for changes in police effort toward hate crime victims. Measures of effort include whether the police came when the incident was reported, if they came within 24 hours, if they confirmed the incident was a hate crime, and if an arrest was made. One concern of large-scale protests is a reduction in time availability for policing which would be evidenced by a reduction in effort for both groups while any change for one group would suggest a change in police bias—positive or negative depending on the sign of the coefficient.

5.3 Mechanism Results

Twitter, TV Headlines, Protests, and Mobility

Correlations between shocks to the treated groups and TV headlines, tweets, and protest measures can be found in Figure 13. Controlling for tweets there is no significant correlation between TV headlines and hate crime with one exception, MSNBC headlines and AWHC. The lack of a strong correlation can be explained by the similarity in profile of a typical hate crime offender and Twitter user: both younger and more male than the average population (McDevitt et al., 2002; Blank, 2017; Wojcik and Hughes, 2019).

The ABHC shock is positively correlated with tweets expressing opposition to the protests, Derek Chauvin's arrest and trial (retaliation), and tweets containing "White genocide" (protectionism), but not with tweets on support for BLM. The significance of the correlation with opposition rather than support follows previous hate crime research finding a spike in hate crime following electoral success of candidates or referendum positions opposing immigration or minorities (Romarri, 2020; Williams et al., 2022). The significant correlation between tweets on police violence toward protesters can be linked to experimental research showing that individuals are sensitive to social cues (and incentives) in shaping cooperation (Boone et al., 2008).

In comparison, AWHC is positively correlated with general tweets on Black Lives Matter and negatively correlated with tweets about Chauvin. The latter indicates that the arrest and trial reduced retaliatory hate crimes attacks against White Americans.

Meanwhile, ABHC and AWHC are positively correlated with past tweets containing the n-word while there is no significant contemporaneous correlation. We also find that contemporaneous or recent use of the n-word is not significantly correlated with the control hate crimes.

Looking at the correlation between protests and hate crime we find that the number of protests–contemporaneous and average in the past week–are significantly correlated with both treated hate crime groups. On the other hand, the number of protesters is negatively correlated with hate crime and may be due to an incapacitation effect. The high correlation of the number of protests compared to protesters reflects the importance of the spread of the protests which were unique to the 2020 BLM protests and the greater threat they posed to enacting policy and social change.

Figure 13d presents the correlations between mobility by location and treated hate crime in the protest period. ABHC and AWHC shocks are both most significantly correlated with residential mobility, followed by workplaces, parks, and markets or pharmacies while the correlation with retail and recreation spaces are negative. This infers that much of the increase occurred in residential areas rather than public spaces such as stores and parks.

Heterogeneity

We next compare the effect of the protests on anti-Black and -White hate crime by region, population size of reporting police force, location of the crime, and crimes against persons or property (see Figures 14-15).

Anti-Black hate crime increased more persistently in the North Central and Northeast compared to the West and South, though the gap in the point estimate is not statistically significant. In comparison, AWHC is comparable across the regions with some evidence of higher persistence in the North Central, the region of Floyd's death.

The increase in ABHC was comparable in magnitude across all population sizes. However, there is evidence that the effect on both treated groups was more persistent in medium-sized municipalities. On the other hand, AWHC was greater in small cities and counties in the first month of the protest.

There is no evidence of changes in the composition of the treated racial hate crime groups with respect to target type (person or property) and offender of the race (15). This is supported in the raw hate crime data which shows that the specific offence type proportions did not change, with intimidation and assault comprising the majority of ABHC and AWHC. The lack of changes in the offence composition is shows that changes in hate crime is not driven by "less serious" offences but rather all degrees of hate crime.

Results by presidential election first show the effect in counties with an increase in share of votes for Donald Trump between 2016 and 2020 relative to counties with a decrease (Figure 16). Areas with an increase in Trump votes experienced a higher AWHC shock and a lower ABHC shock compared to areas with a decrease in Trump voting share. Moreover, compared to counties that voted for Trump in 2016, counties won by Hillary Clinton had a larger increase in hate crimes against both groups in most time periods. However, the results are suggestive as the 2020 elections occured after the protests and protests had significant positive effect on Democratic voting

(Klein Teeselink and Melios, 2021). There are two possible explanations for the latter results. First, Democrat voters responded more strongly to the protests with respect to committing hate crimes. Second, xenophobes in Democrat areas responded more strongly due to greater concern of policy changes such as reduced police budget more supported by democratic politicians.

Of the four demographic measures[11] the largest difference in treatment effect is observed based on changes in unemployment rates between 2019 and 2020 (Figure 17). We find that areas with an above average increase in unemployment witnessed relatively larger increases in ABHC and AWHC with comparable gaps between the two treated groups.

In comparison, the differences between high and low areas based on income, share with a college degree, and Black population vary by ABHC and AWHC. For income and college degrees, counties with above average values experience relatively higher shocks to ABHC but lower shocks to AWHC. The inverse is generally found for areas with a high Black population. The larger effect in more-educated areas is supported by research finding greater support among the more-educated for Hezbollah and Israeli settlers attacks on Palestinians in the West Bank (Krueger and Malečková, 2003) and Ku Klux Klan membership in the 1920s (Fryer and Levitt, 2012). Holder et al. (2022) find that anti-Black hate crime is lower in counties with more concentrated disadvantage and Gladfelter et al. (2017) find that ABHC is higher in advantaged communities and the inverse for AWHC.

ABHC shock was lower in counties with a higher Black population while the inverse was found for AWHC. This is supported in previous research finding that ABHC is more common in homogeneous and advantaged White communities (Gladfelter et al., 2017) while AWHC incidents increased over time most in largely Black communities in New York City (Mills, 2020).

Next, the effect of the protests are separated by the history of racial-justice protests in the county. The data is aggregated by counties with a protest prior to Floyd's death, first protest occurring following the death, and counties without any protests at all (see Figure 19). We find weak evidence that the hate crime shock was greater and more-precisely estimated in areas with first protests, though all areas experienced an increase. The increase was greatest in the height of the protests, when these first protests were most likely to occur.

In a final heterogeneity by location characteristic, the mediating effect of the

[11] Additional heterogeneity analysis by unemployment levels and other education measures available on request but do not produce significant results.

COVID-19 pandemic is analysed by looking at difference between areas based on policy stringency and economic support. There is no evidence that states with more stringent policies experienced a larger hate crime shock. Finally, states providing more economic support during the pandemic experienced greater hate crime shocks against both groups.

Comparison to other events
Compared to past deaths, the protests of 2020 had a significantly larger positive effect on racial hate crimes (Figure 20). We find evidence that responses to deaths follow similar patterns for anti-Black and -White hate crime. However, compared to the 2020 protests the relative change in victimization probability is higher for AWHC. This could be due to retaliation against White Americans without a large response in anti-Black hate crime. The latter is explained by fewer anti-racism protests subsequent to these deaths, minimizing the mechanisms of protectionism and retaliation.

Responses to previous salient deaths do not follow a clear pattern and indicate that there are mediating factors. The first deaths to lead to a significant response were in close succession and suggests that reporting of multiple deaths in 2015 plus the rise of the BLM movement in 2014 combined increased racial hate crime. The death of Tamir Rice preceded a significant decrease in hate crime. Compared to other deaths this is unique in that it was a death of a child and occurred in colder season near a major holiday (Thanksgiving).

Reporting
The reporting probability of Black Americans who are hate crime or non-biased crime victims did not increase significantly in the post period (see Figure 21). Reporting probability of AWHC did significantly increase at the time of the protests by 31 percentage points (75 percent increase compared to pre-treatment average). Given that AWHC increased by over 4 crimes per day (around 225 percent) this implies that the change in reporting probabilities can explain one-third of the observed change in anti-White hate crime.

There is weak evidence that police reduced effort toward victims of ABHC ($p < 0.10$) but no evidence of a similar reduction for victims of anti-White hate crime. Rather than evidence of a Ferguson effect, these results suggest anti-racism or anti-police violence protests lead to a reduction in police effort toward hate crimes against the protesting group. This is first evidence of a change in response by police to racial hate crime but can be connected to existing literature finding positive effects of Trump rallies on police bias against Black drivers (Grosjean et al., 2022). It is also possible that response to ABHC reduced due to fear of police officer's safety, however we find no change in response to all crimes against Black Americans.

Characteristics of the offenders for the most part did not significantly change during the protests. The only exception is that offenders of anti-White hate crime were more likely to not be strangers to the victim. There is weak evidence that offenders of ABHC were more likely to be younger and offend in groups, though it is imprecisely estimated due to the low number of ABHC with information on the offender in the NCVS.

Figure 22 presents robustness checks to the analysis of the crime victimisation survey data. These robustness checks include using a global RD model with triangular kernel weights and placebo-in-time test using June 2019 as the treated period. Both robustness checks confirm and validate the baseline findings, respectively.

6 Conclusion

We provide first evidence of the impact of anti-racism protests on racial hate crimes. Following the nascent of the 2020 Black Lives Matter protests in the United States as a reaction to the murder of George Floyd on 25 May 2020 recorded anti-Black and -White hate crime increased by 260 and 165 percent in June, respectively, and remained elevated throughout the summer.

The relative effect of the 2020 BLM protests on racial hate crime is significantly greater than the effects of terrorism and the EU referendum on hate crime in the UK, as well as 9/11 and Trump's election in 2016 in the US. The smaller observed effects in the UK may reflect differences in hate crime collection and definition as well as dampened treatment effects. However, Americans responded more strongly to BLM protests then they did to past elections, terrorism, and COVID (Asian hate crime increased from 77 in 2019 to 167 in 2020). In addition to the historical context of Black-White race relations and higher unemployment, the difference is likely due to larger threat of the minority group–in part due to majority group allies–and perceived cues from the police. The former increases the benefit of hate crime while the latter would decrease expected criminal justice costs.[12]

Results of the heterogeneity analysis suggest that changes in unemployment during the pandemic is the most significant mediating factor. Moreover, there is evidence

[12]For example, UK prosecutors announced an augmentation of hate crime sentences in response to the post-Brexit hate crime shock.

that the shock was larger and more persistent in areas most treated by the protests as measured by first protests and area size.

Characteristics of victimization and hate crimes also changed during the protests. While Black victims did not change behavior, White victims were more likely to report victimization to the police. For their part, there is evidence to suggest that in response to the protests police reduced effort toward anti-Black hate crime and increased arrests of anti-White hate crime offenders.

One limitation of this research is hate crime data from the US. Hate crime itself has different definitions across jurisdictions and makes it difficult to compare levels between areas. This is compounded by the fact that the choice to strictly define and record hate crime is endogenous to the demographics and social norms of the region. While we are interested in short-run effects and find no evidence of changes in hate crime laws or collection during the protest, it is possible that recording of hate crime increased due to public scrutiny toward police. However, given the evidence that police reduced effort toward ABHC victims it is more probable that the effect of the protests is underestimated in the recorded data.

The findings of this research have important implications for policy makers. First, in the event of racial protests additional attention and care is needed for the protesting minority group and majority group. Second, violence against protesters by the police is a strong predictor in hate crime shocks which should be considered in the police response to protests. This brings to the forefront research on how law enforcement can effectively police protests by "engaging rather than enraging the crowd" (Brown, 2015), building public trust, and improving training in deescalation and preparation (Shaw et al., 2015). Investigation of the NYPD's response to the protests reveal that the department lacked a clear strategy, used excessive force which "contributed to heightened tensions", and lacked training and community engagement.[13]. Furthermore, a 2015 federal inquiry into 21st century recommends "[minimizing] the appearance of a military operation and avoid using provocative tactics and equipment that undermine civilian trust" (Kearns et al., 2015).

Another concern for policy makers and researchers is the relationship between recent online hate speech and hate crime. This research finds evidence to suggest that the reports of an increase in online anti-Black, homophobic, and transphobic hate speech on Twitter following its purchase by Elon Musk (Benton et al., 2022) and

[13]Report on NYPD's response to the protests https://www.nytimes.com/interactive/2021/03/20/us/newyork-policing-DOI.html

a reduction in removal of illegal hate speech on social media in 2022[14] can lead to an increase in hate crime. More research and data is needed to understand the effect of online hate speech and if online behavior can be used to predict hate crime spikes.

Finally, social norms discouraging hate crimes against majority and minority groups must be projected by public figures and the media during racial conflict to avoid hate crime contagions. In broader terms the results show that by raising the saliency of racism, social justice movements make themselves more vulnerable to retaliatory and protectionist hate crimes. Though COVID-19 is a unique event results indicate that it is economic insecurity rather than pandemic policy stringency that mediated the effect of the protests. This research is therefore broadly applicable to any time of high unemployment.

While we use the 2020 BLM movement to illustrate the effect of mass protests on racial hate crime, the findings could be extended to any large-scale social conflict between majority and minority groups including faith, sexuality, or gender. With the rising polarity in the US, future conflict between opposing groups over an emotional subject is likely. This research suggests that in the absence of positive intervention the conflict increases the occurrence of a hate crime shock.

[14] https://www.cbsnews.com/news/twitter-other-social-media-slip-on-removing-hate-speech-european-union-review/

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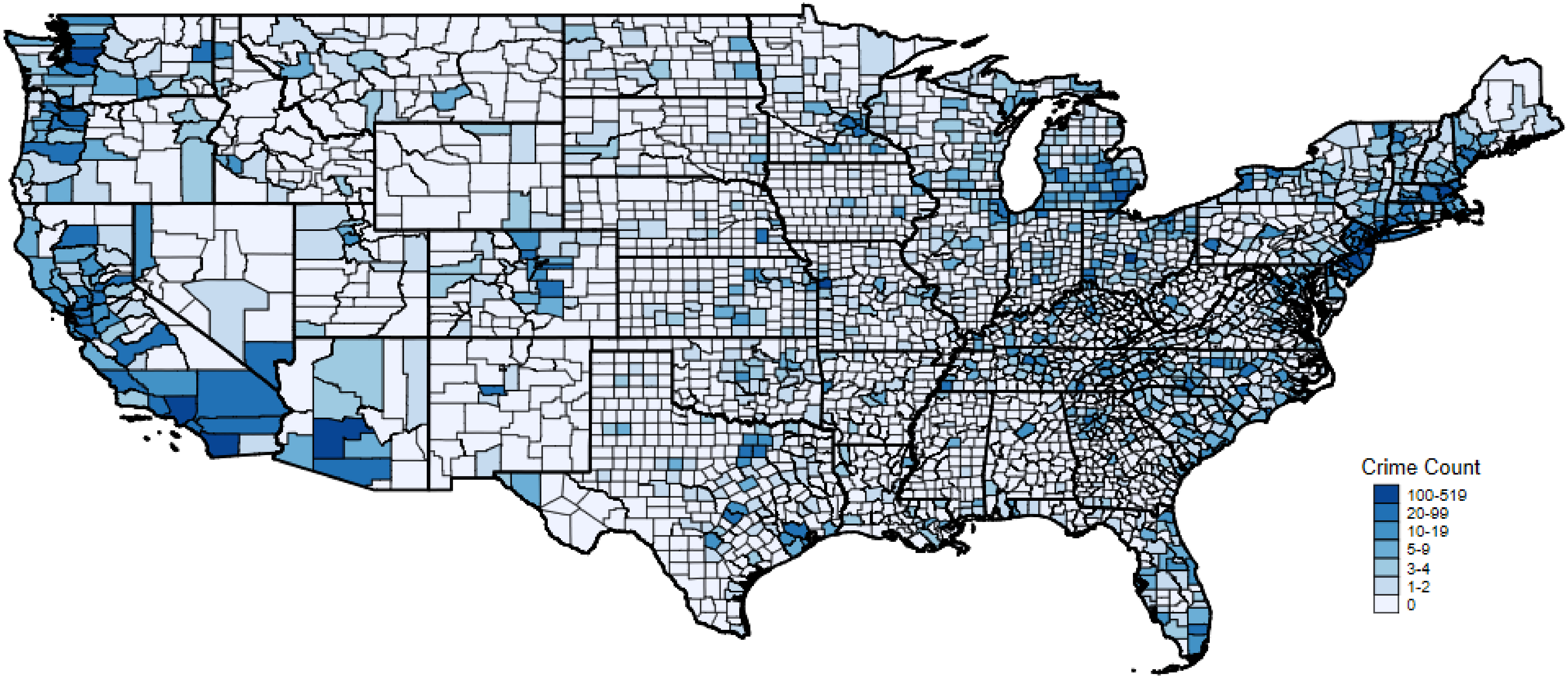
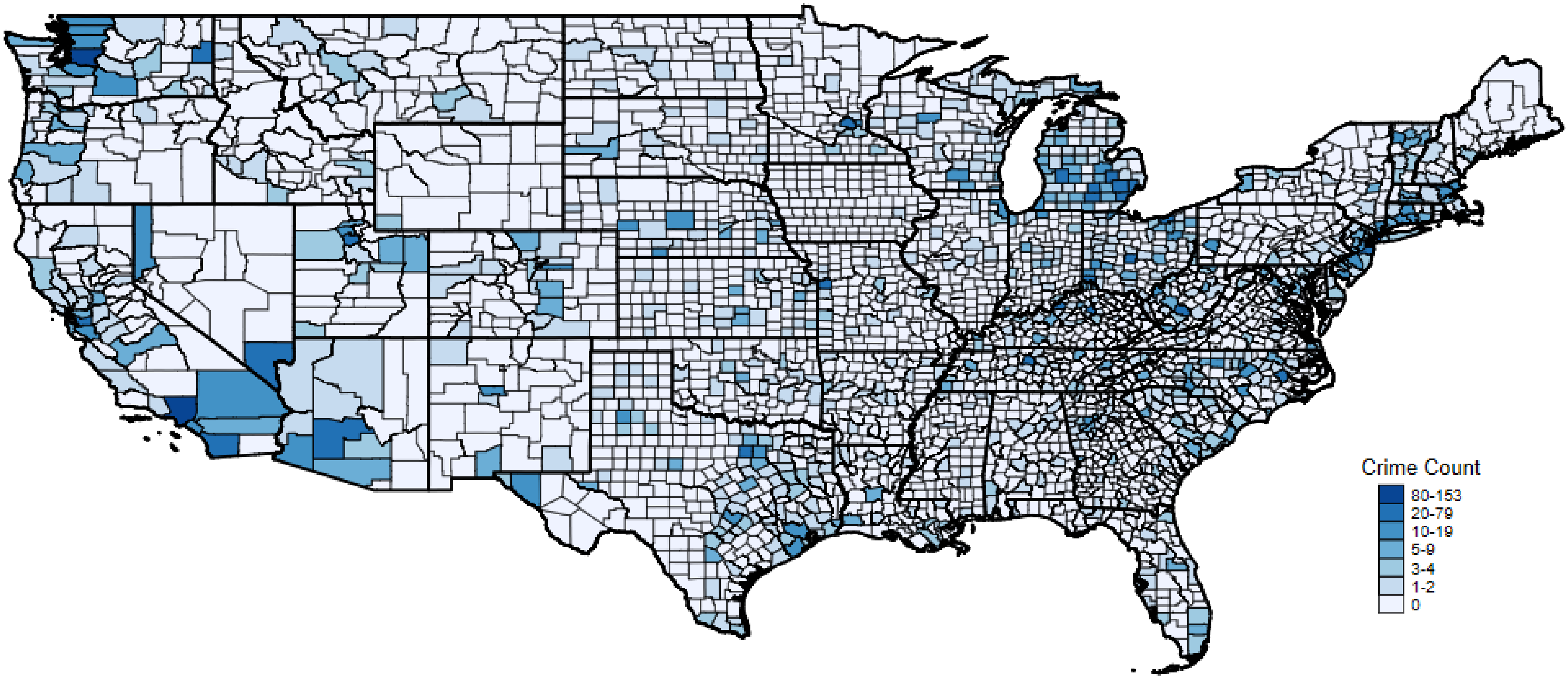
Figure 1: Anti-Black Hate Crime Map, 2016-2020



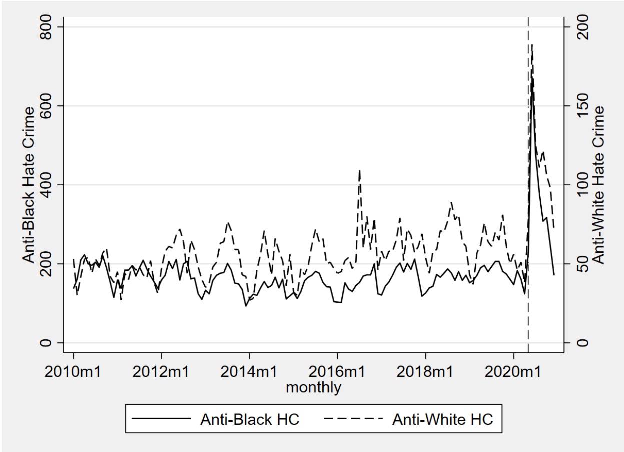
Source: Recorded crime data from the FBI's Uniform Crime Report.

Figure 2: Anti-White Hate Crime Map, 2016-2020

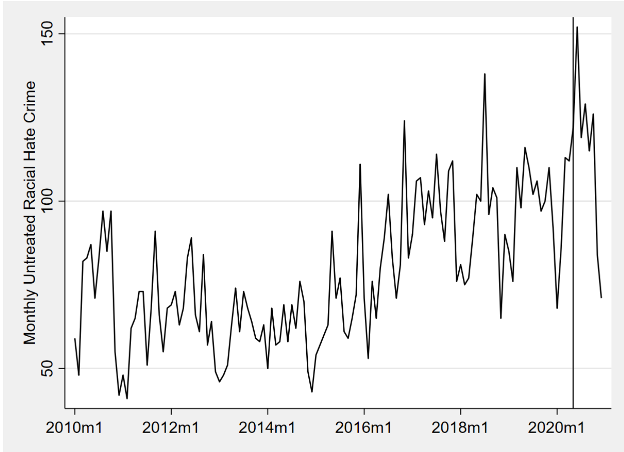


Source: Recorded crime data from the FBI's Uniform Crime Report.

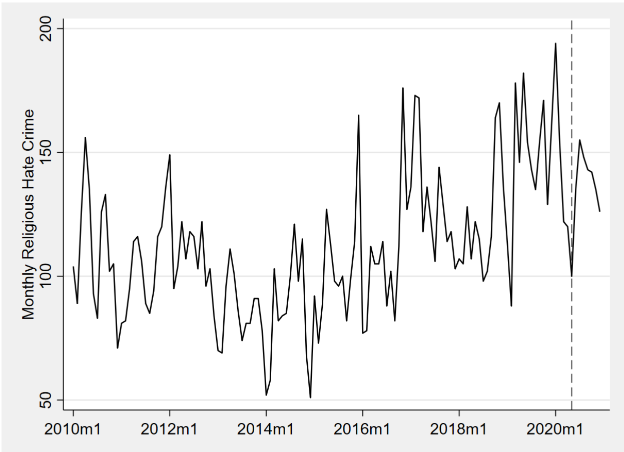
Figure 3: Monthly Time Series - Hate Crime Data



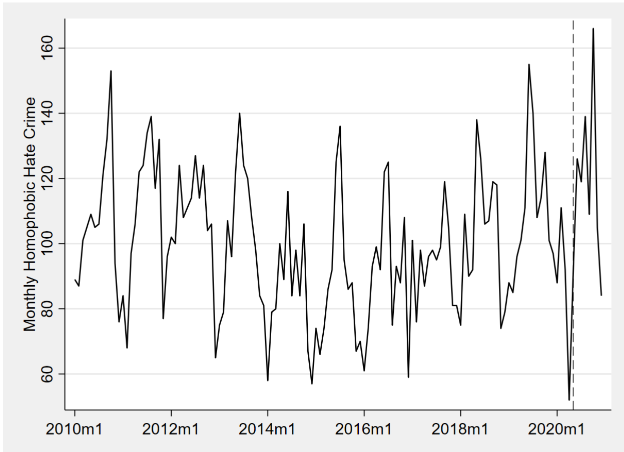
(a) Treated Hate Crime



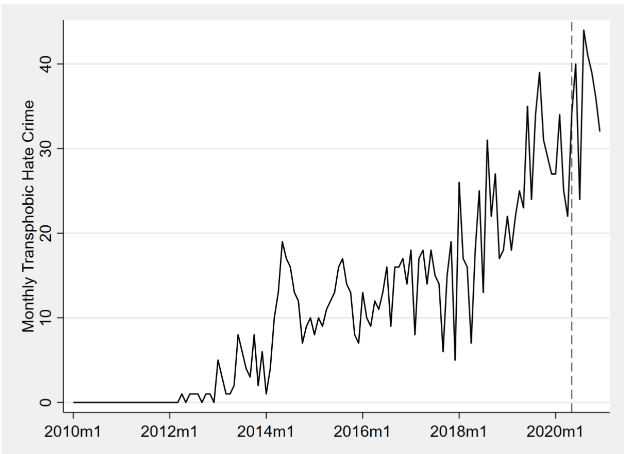
(b) Untreated Racial Hate Crime



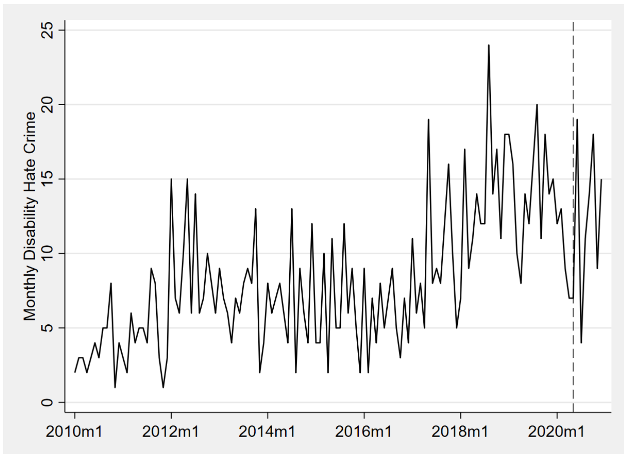
(c) Religious Hate Crime



(d) Homophobic Hate Crime



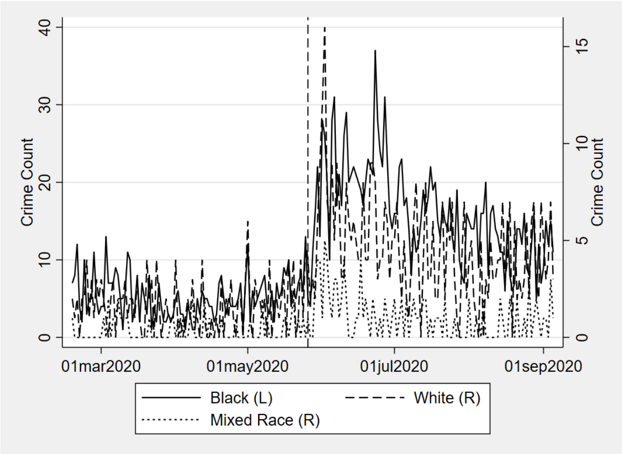
(e) Transphobic Hate Crime



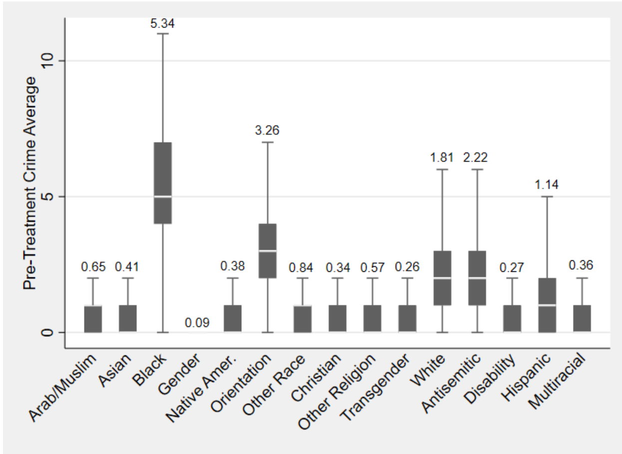
(f) Disability Hate Crime

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Monthly count of hate crime, 2010-2020. Racial hate crime excludes anti-Black hate crime.

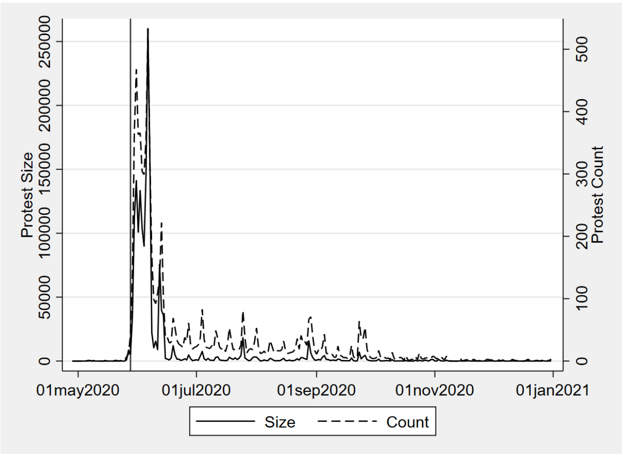
Figure 4: Summary Statistics



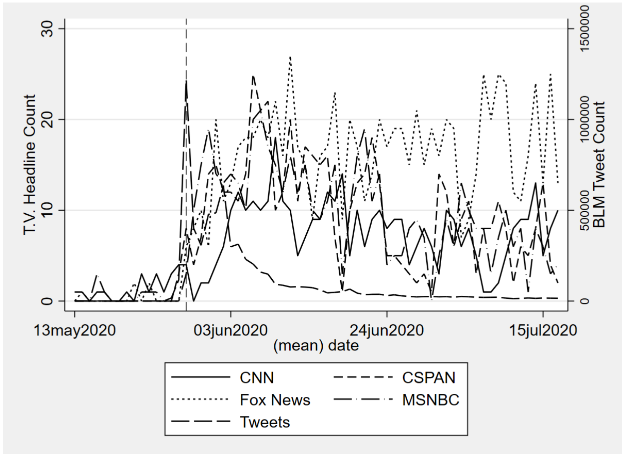
(a) Daily Treated Racial Hate Crime



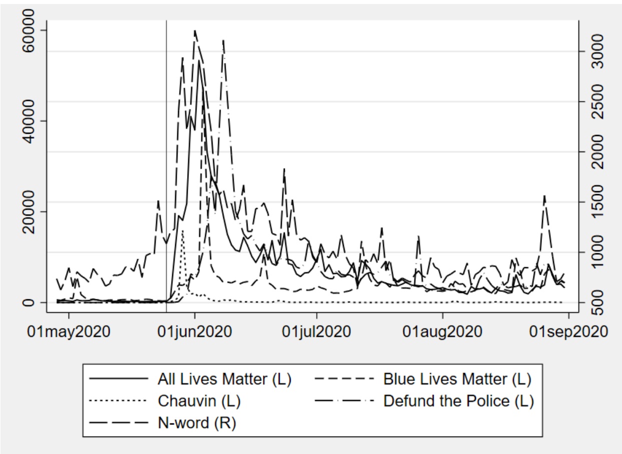
(b) Box Graph By Hate Crime



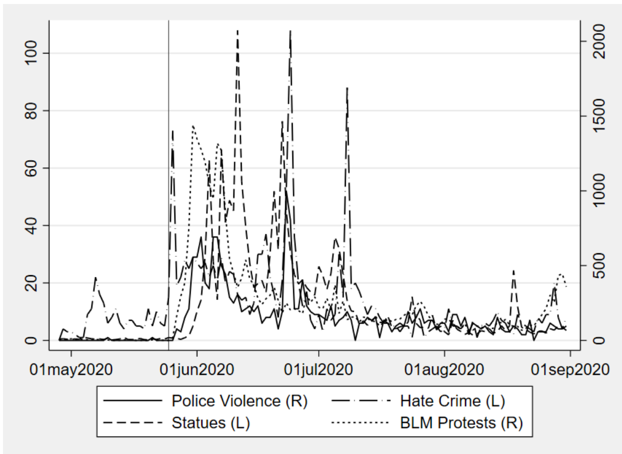
(c) Protest Size and Count



(d) Media



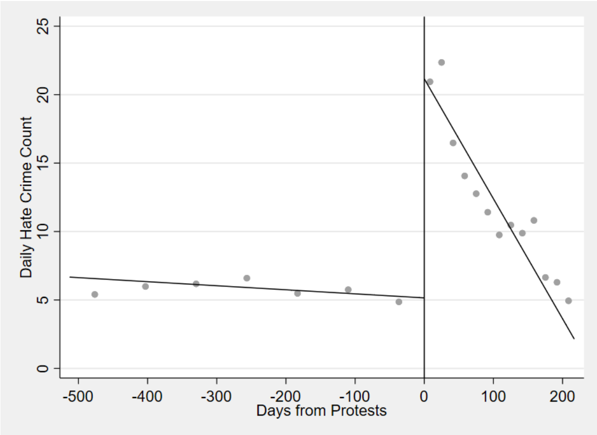
(e) Daily Tweet Count



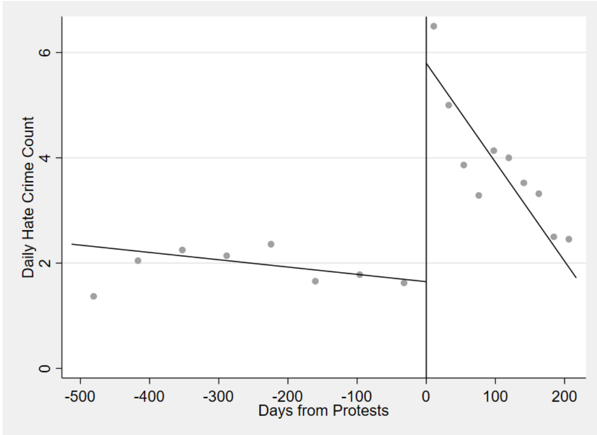
(f) Daily Tweet Count

Source: Panels (a-b): Recorded crime data from the FBI's Uniform Crime Report. Panel (c): Count Love protest data https://countlove.org/. Panel (d): Search of T.V. headlines with "Black lives matter" on archive.org and author's own calculations. Panels (e) and (f) Author's own calculations.
Notes: Panels (a) and (b): Time series of deseasonalised and detrended racial hate crime by ethnic or racial group. Solid black line captures the residual for anti-Black hate crime while the other lines are for the control racial hate crime groups. For the U.S. data the right y-axis is for anti-Black hate crime and the left y-axis is for the three control crimes due to the substantial increase following the onset of the protests.

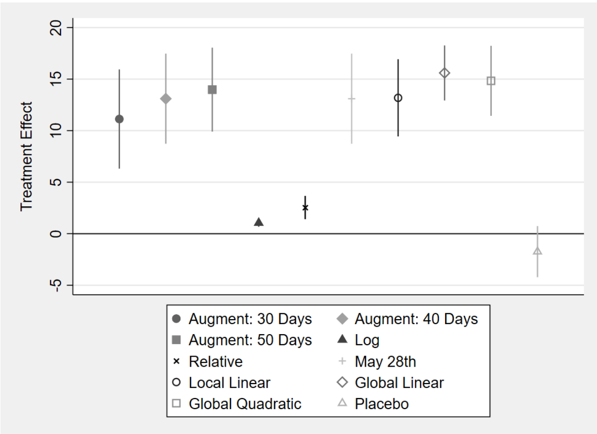
Figure 5: Anti-Black and Anti-White Racial Hate Crime - RD Results



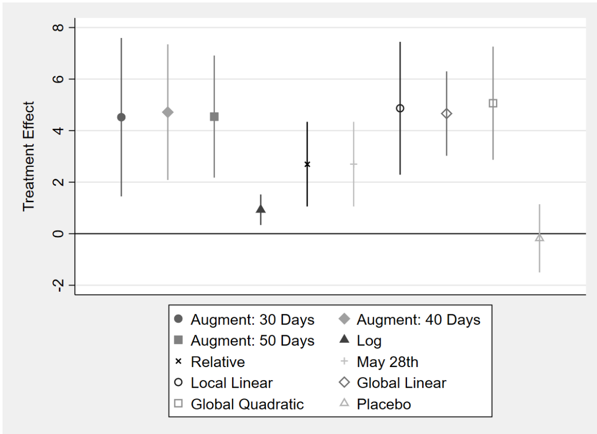
(a) RD Plot: Anti-Black Hate Crime



(b) RD Plot: Anti-White Hate Crime



(c) Anti-Black Hate Crime

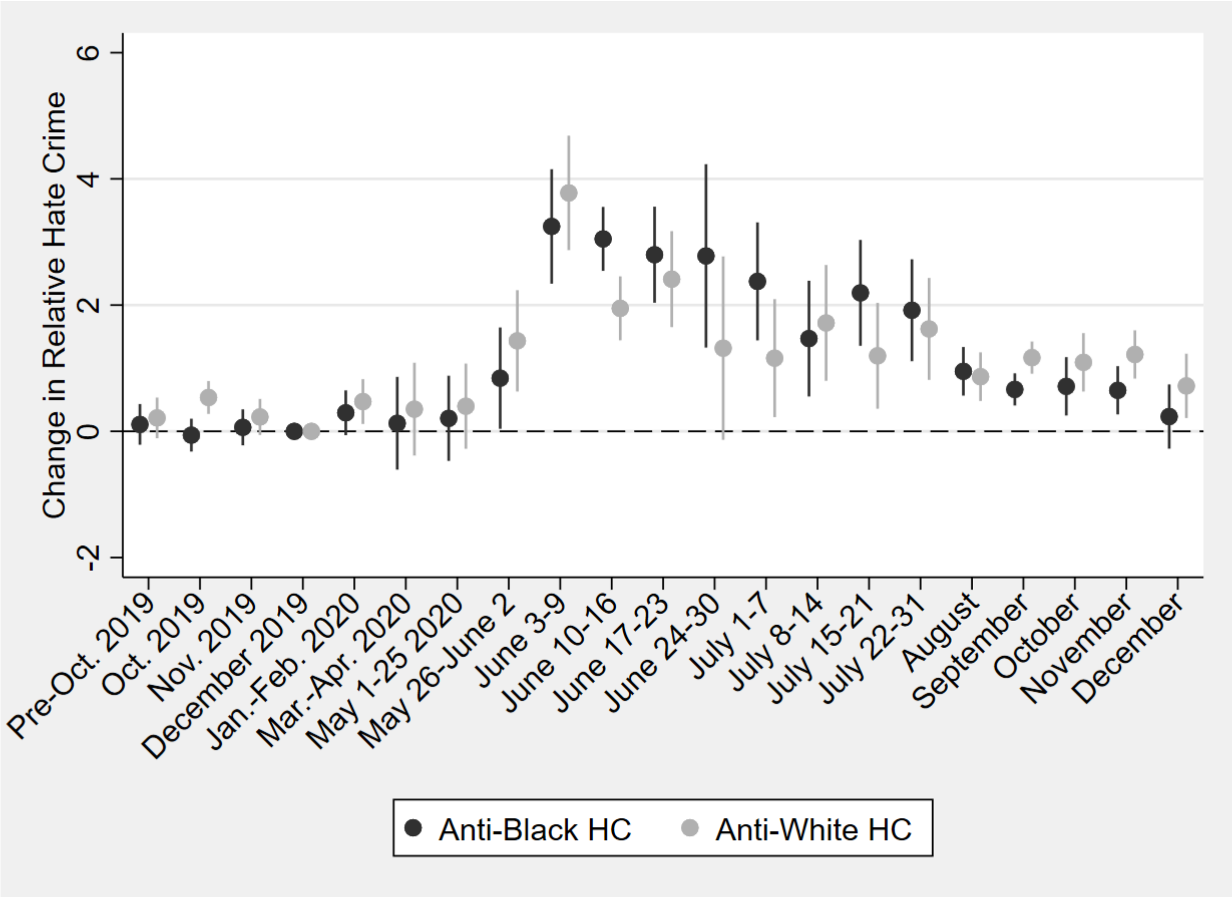


(d) Anti-White Hate Crime

Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Each line represents a different regression discontinuity in time difference-in-differences specification. The first three are the baseline local augmented model with bandwidths of 30, 40, and 50 days, respectively. The fourth and fifth are alternative crime measurements, log and relative deviation to average. The sixth uses an alternative cutoff dates, May 28th. The eighth and ninth estimates are for a local linear and global linear RD model. The ninth is a global polynomial estimation. The final specification is a placebo in time test using 26 May 2019 as the discontinuity. **Panel (c)**: Treated group is anti-black hate crime and the control groups are other groups or biases. **Panel (d)**: Treated group is anti-White hate crime and the control groups are other groups or biases.

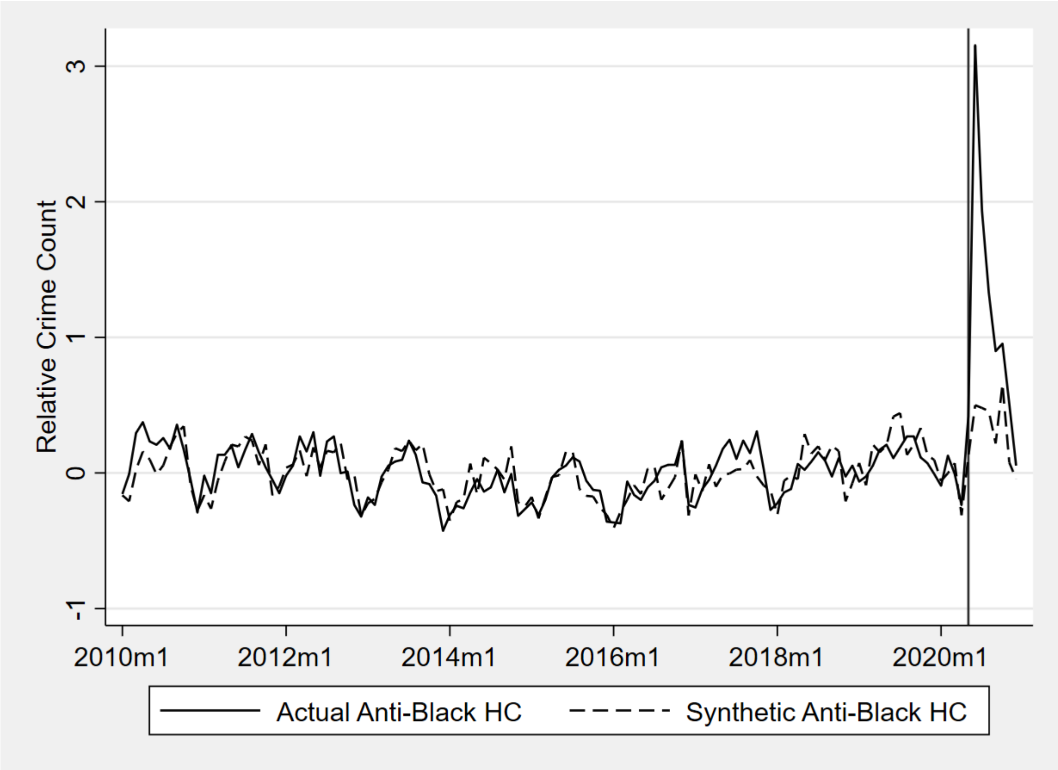
Figure 6: ES Baseline Results



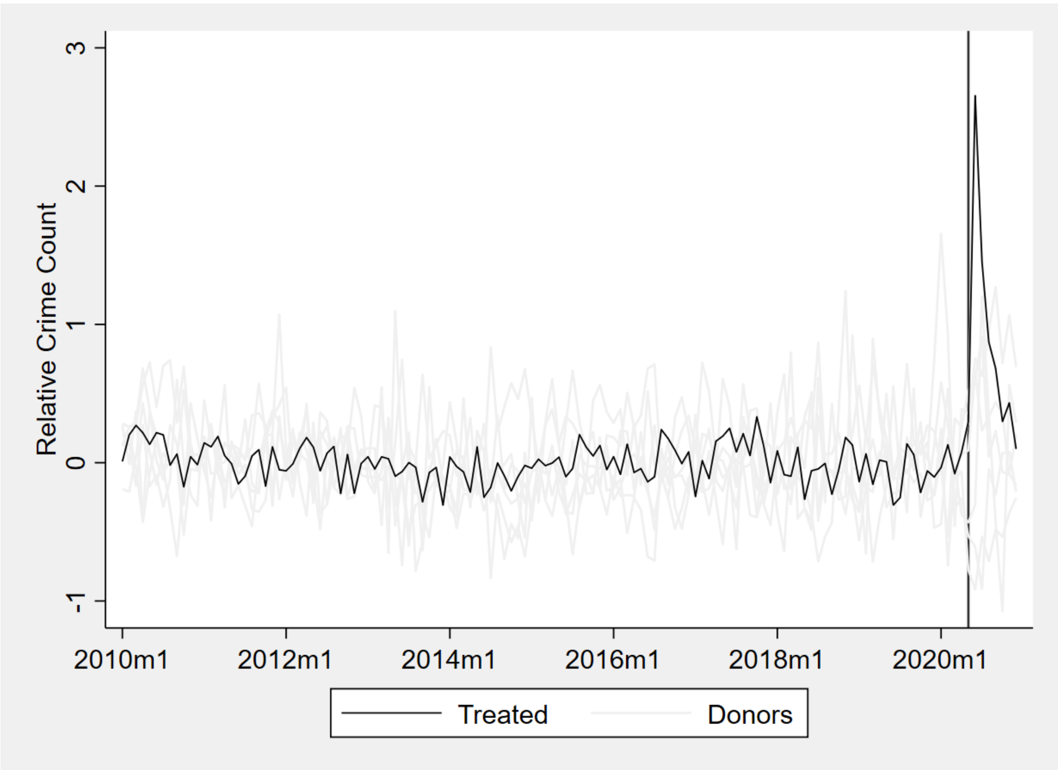
(a) Event Study

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated groups are anti-Black and anti-White hate crime and the control groups are other groups and biases. The baseline time period is December 2019.

Figure 7: Anti-Black Racial Hate Crime - Synthetic Control Results



(a) SCM: Treatment

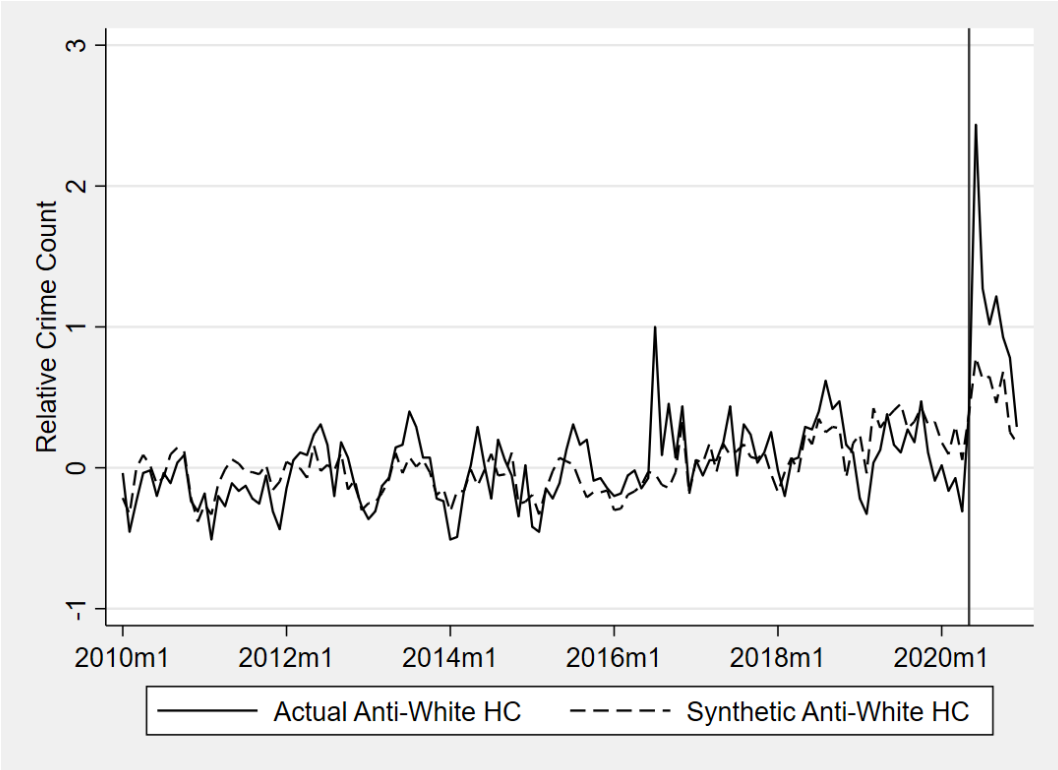


(b) SCM: Placebos

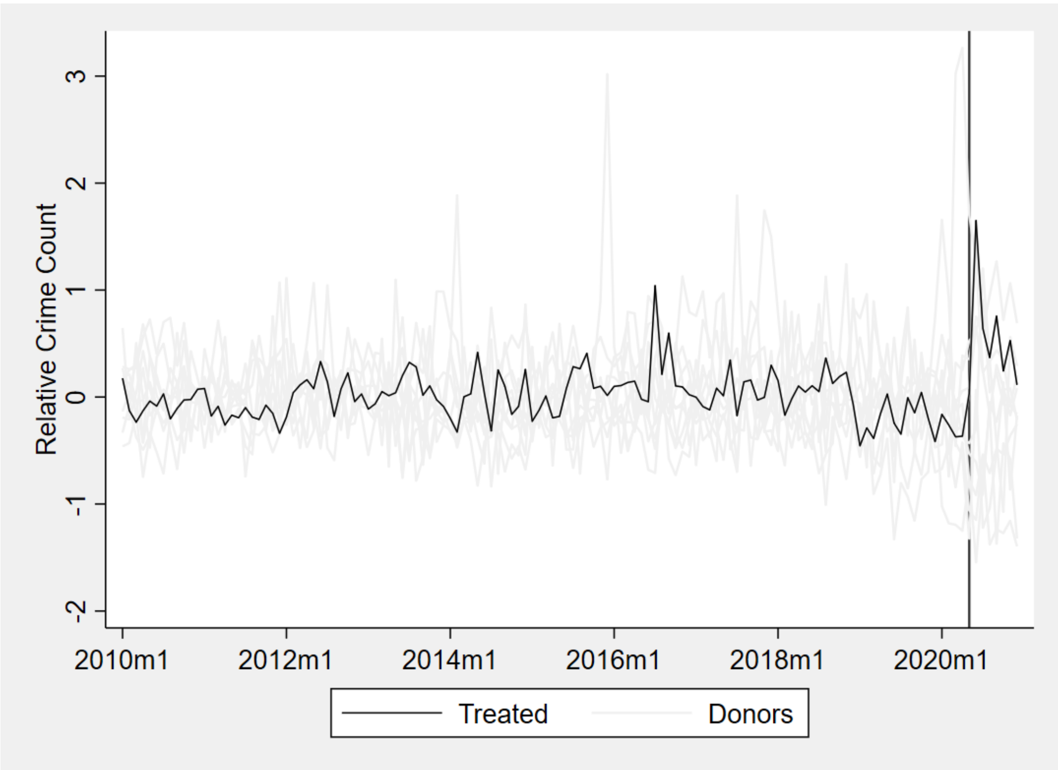
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated group is anti-Black hate crime and the control groups are other groups and biases. The matching period is May 2016 to December 2019.

Figure 8: Anti-White Racial Hate Crime - Synthetic Control Results



(a) SCM: Treatment

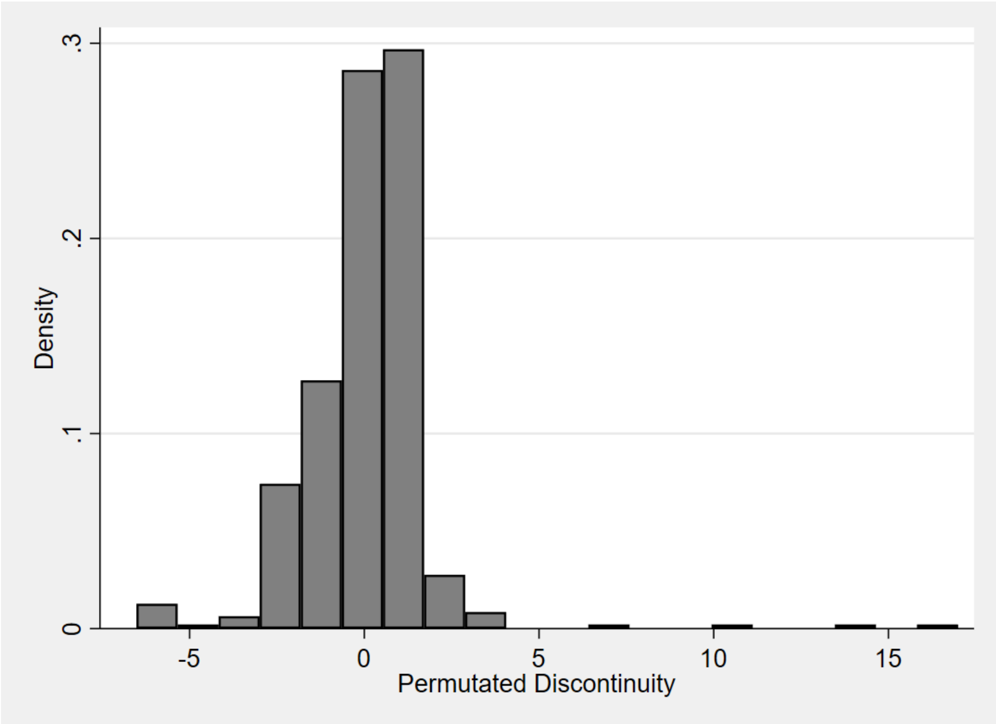


(b) SCM: Placebos

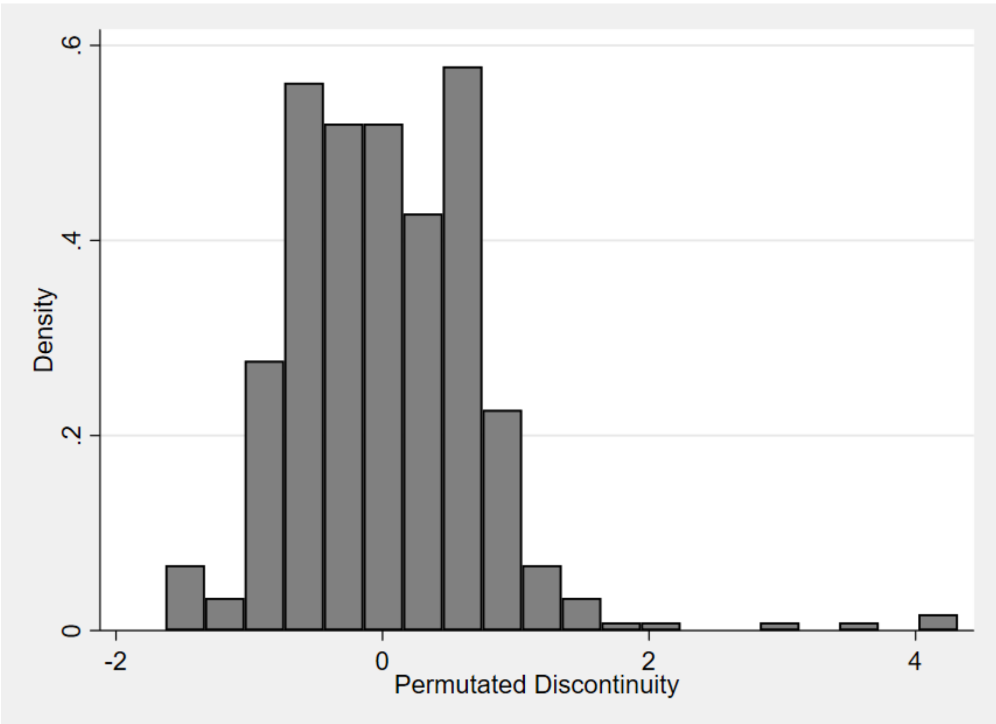
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated group is anti-White hate crime and the control groups are other groups and biases. The matching period is May 2016 to December 2019.

Figure 9: RD Robustness: Permutations



(a) Anti-Black Hate Crime

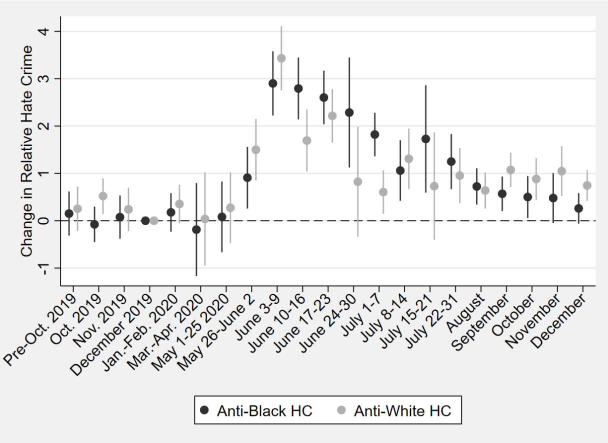


(b) Anti-White Hate Crime

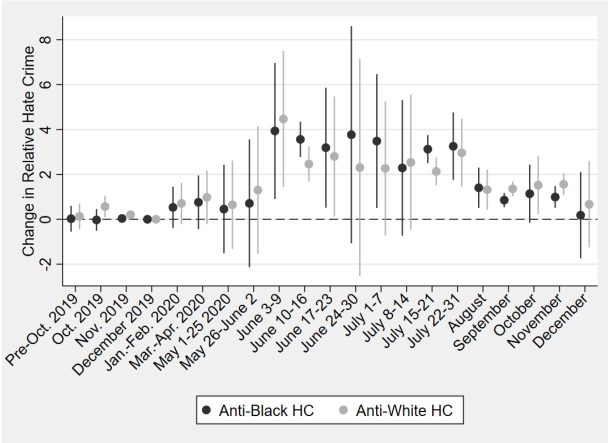
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Distribution of permutated discontinuities for (a) anti-Black and (b) anti-White hate crime using daily crime count as the outcome variable. Permutations consist of every two days going back 2000 days prior to (and including) the actual discontinuity on 26 May 2020.

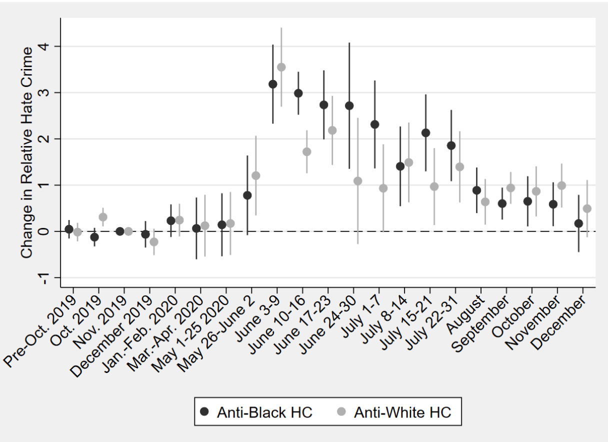
Figure 10: ES Robustness Results



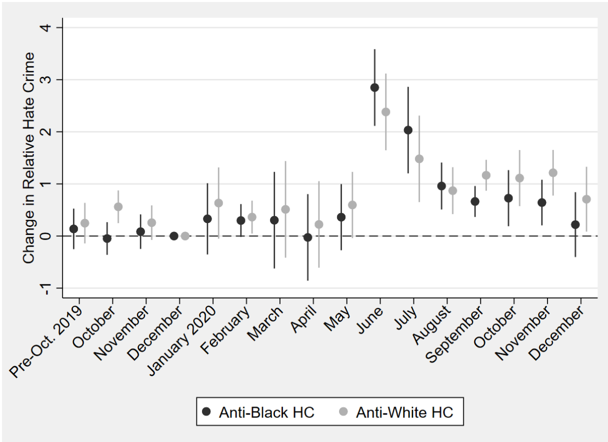
(a) Race Controls Only



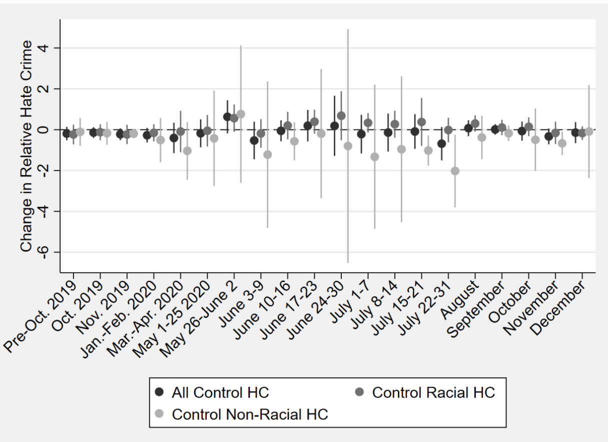
(b) Non-Race Controls Only



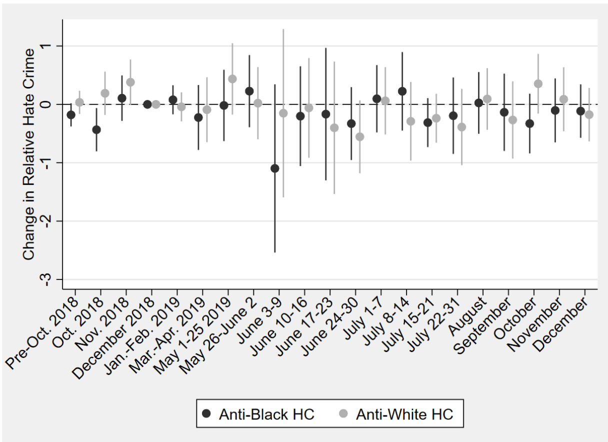
(c) Alternative Baseline



(d) Monthly Data



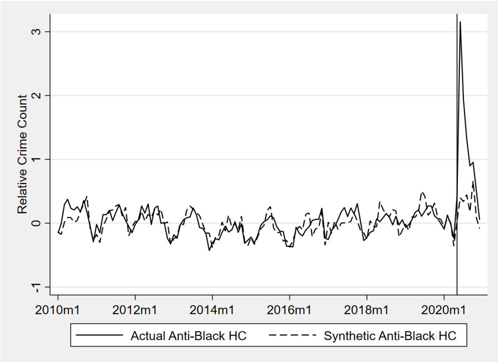
(e) Substitution Effects



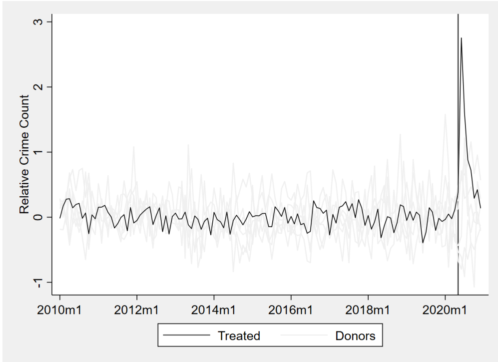
(f) Placebo in Time: 2019

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). **Panel (a)**: The baseline time period is December 2019. The treated groups are anti-Black and anti-White hate crime and the control groups are other racial/ethnic groups. **Panel (b)**: The baseline time period is November 2019. The treated groups are anti-Black and anti-White hate crime and the control groups are other racial/ethnic groups and biases. **Panel (c)**: The baseline time period is December 2019. The treated groups are all control hate crimes, racial control hate crimes, and non-racial control hate crimes. **Panel (d)**: The baseline time period is December 2018. The treated groups are anti-Black and anti-White hate crime and the control groups are other racial/ethnic groups and biases.

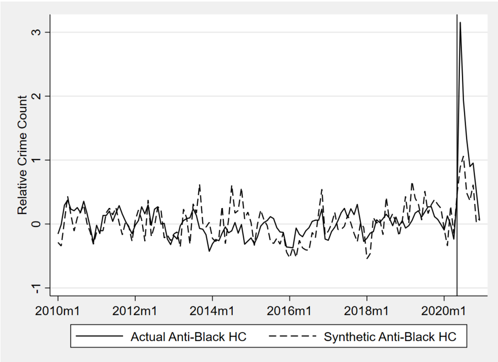
Figure 11: SCM Robustness: ABHC



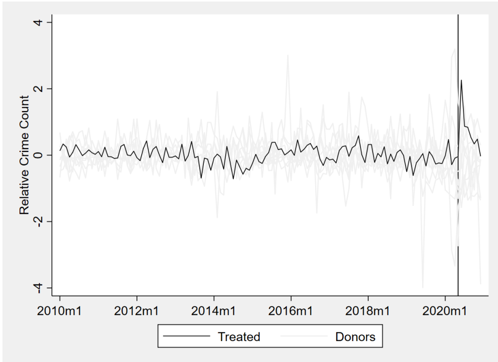
(a) SCM 3 Yr Matching: Treatment



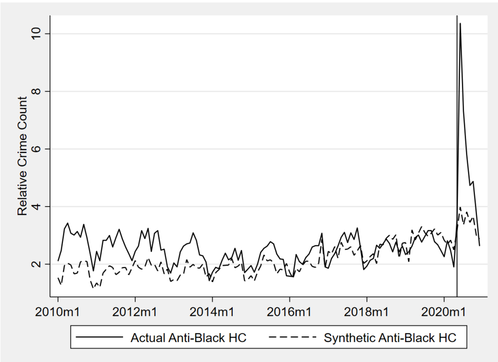
(b) SCM 3 Year Matching: Placebos



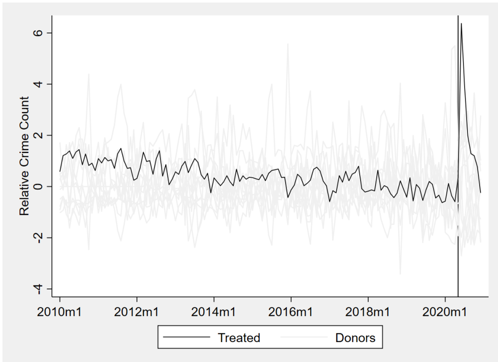
(c) SCM No Homophobia: Treatment



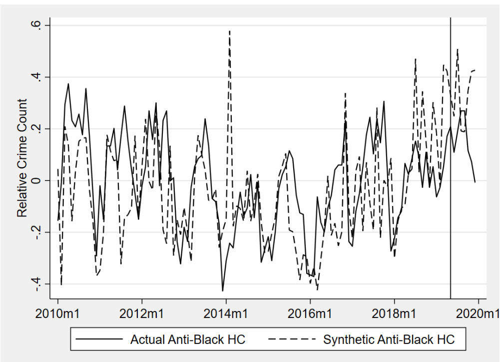
(d) SCM No Homophobia: Placebos



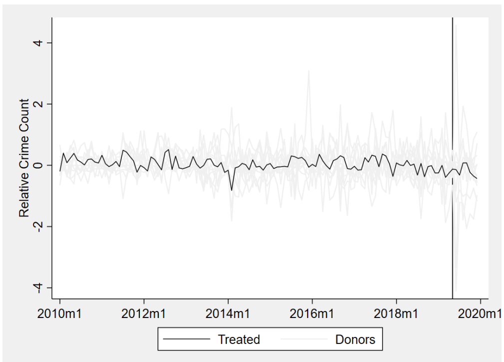
(e) SCM Std. Dev: Treatment



(f) SCM Std. Dev: Placebos



(g) SCM Placebo in Time: Treatment

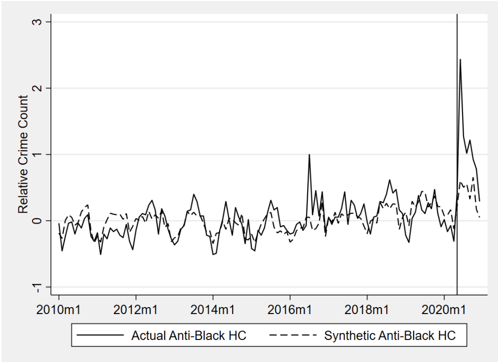


(h) SCM Placebo in Time: Placebos

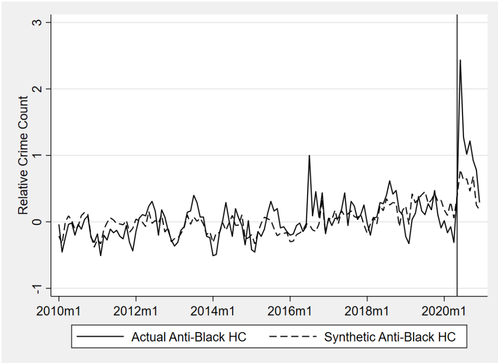
Source: Recorded crime data from the FBI's Uniform Crime Report.

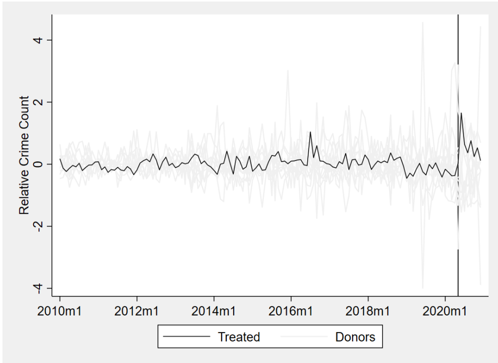
Notes: **Panels (a-b)**: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated group is anti-Black hate crime and the control groups are other groups and biases. The matching period is January 2017 to December 2019. **Panels (c-d)**: The treated group is anti-Black hate crime and the control groups are other groups and biases excluding homophobic hate crime. The matching period is May 2016 to December 2019. **Panels (e-f)**: Outcome variable is measured as crime count relative to the pre-treatment standard deviation. The treated group is anti-Black hate crime and the control groups are other groups. The matching period is May 2016 to December 2019. **Panels (g-h)**: Treatment lasts May-December 2019 with matching period three years prior.

Figure 12: SCM Robustness: AWHC

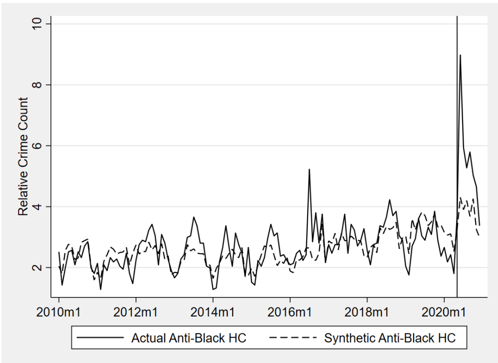


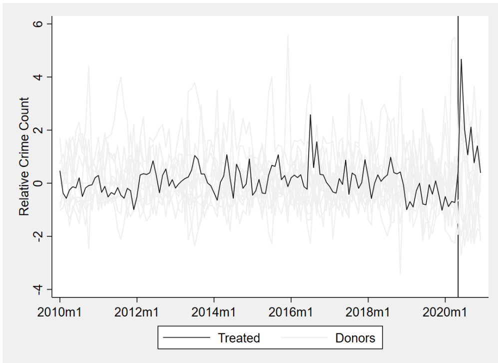
(a) SCM 3 Yr Matching: Treatment (b) SCM 3 Year Matching: Placebos



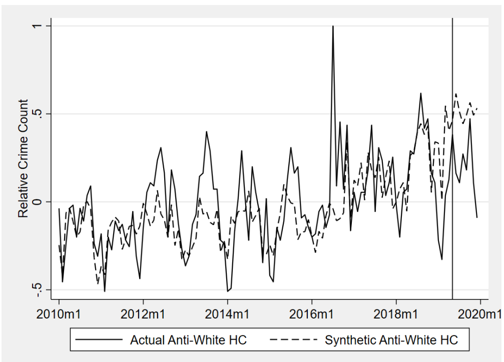


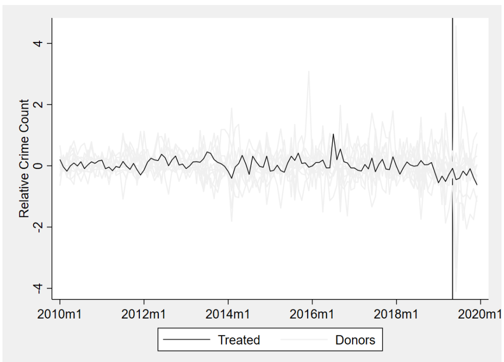
(c) SCM No Homophobia: Treatment (d) SCM No Homophobia: Placebos





(e) SCM Std. Dev: Treatment (f) SCM Std. Dev: Placebos



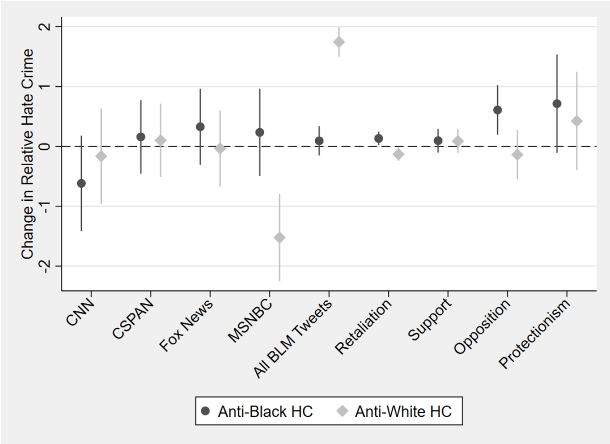


(g) SCM Placebo in Time: Treatment (h) SCM Placebo in Time: Placebos

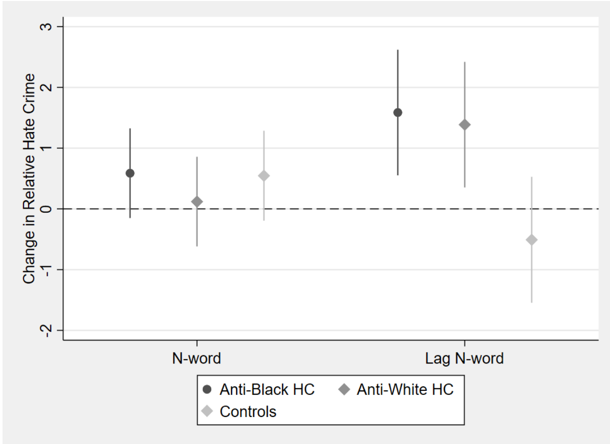
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: **Panels (a-b)**: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated group is anti-Black hate crime and the control groups are other groups and biases. The matching period is January 2017 to December 2019. **Panels (c-d)**: The treated group is anti-Black hate crime and the control groups are other groups and biases excluding homophobic hate crime. The matching period is May 2016 to December 2019. **Panels (e-f)**: Outcome variable is measured as crime count relative to the pre-treatment standard deviation. The treated group is anti-Black hate crime and the control groups are other groups. The matching period is May 2016 to December 2019. **Panels (g-h)**: Treatment lasts May-December 2019 with matching period three years prior.

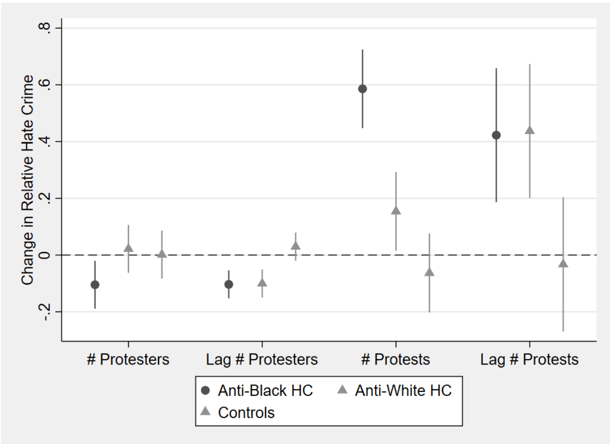
Figure 13: Mechanisms



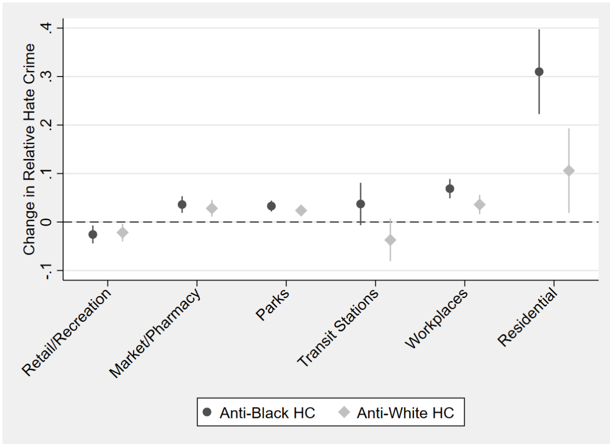
(a) Media



(b) N-word Tweets



(c) Protests

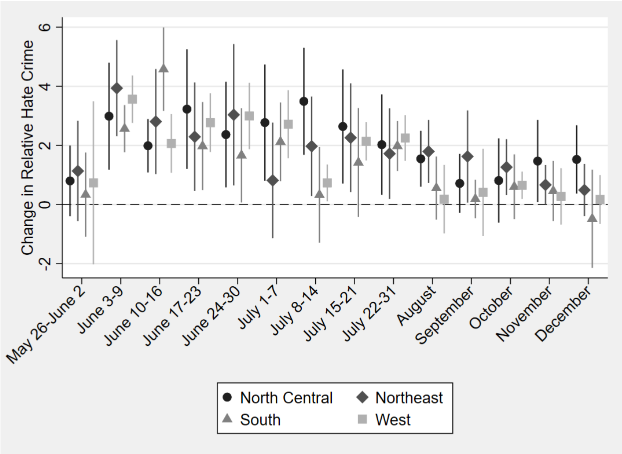


(d) Mobility

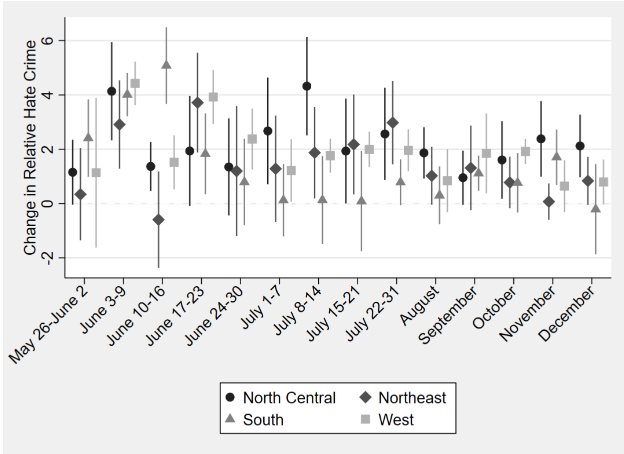
Source: Recorded crime data from the FBI's Uniform Crime Report. T.V. headlines data from archive.org search for "Black Lives Matter". Author's own calculations.

Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). **Panel (a)**: Coefficients capture the difference in the correlation between the control groups (other ethnic groups and biases) and anti-Black and -White hate crime. Variables of interest measure the log-transformed average count of T.V. headlines and tweets. **Panel (b)**: Correlation between hate crime and (lag) log number of tweets containing the n-word. **Panel (c)**: Correlation between hate crime and (lag) daily estimated number of protesters and (lag) daily number of protests held. **Panel (d)**: Coefficients capture the difference in the correlation between the control groups (other ethnic groups and biases) and anti-Black and -White hate crime with mobility to types of locations.

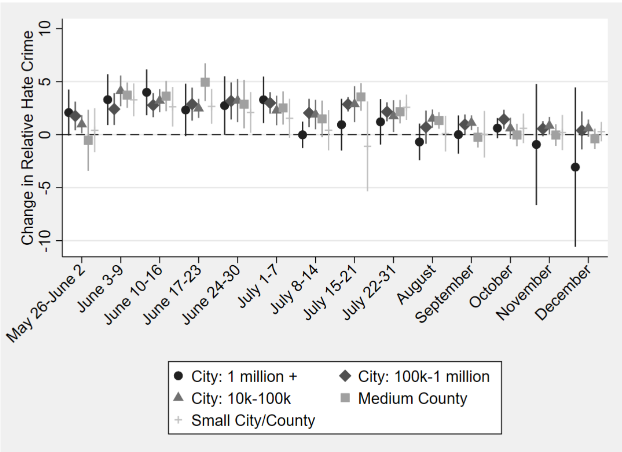
Figure 14: Results by Region and Location Size, ES



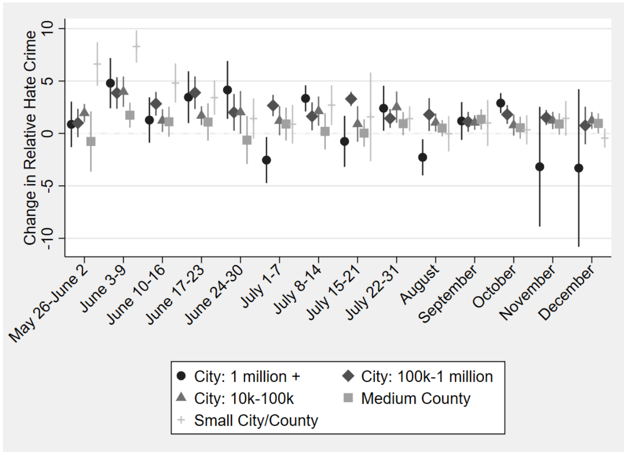
(a) Region: Anti-Black HC



(b) Region: Anti-White HC



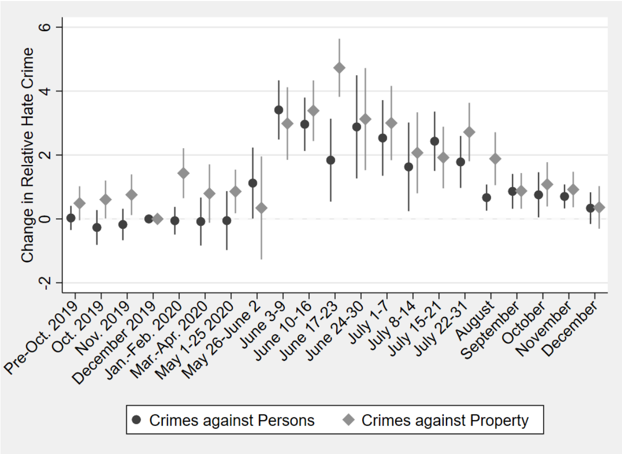
(c) Size: Anti-Black HC



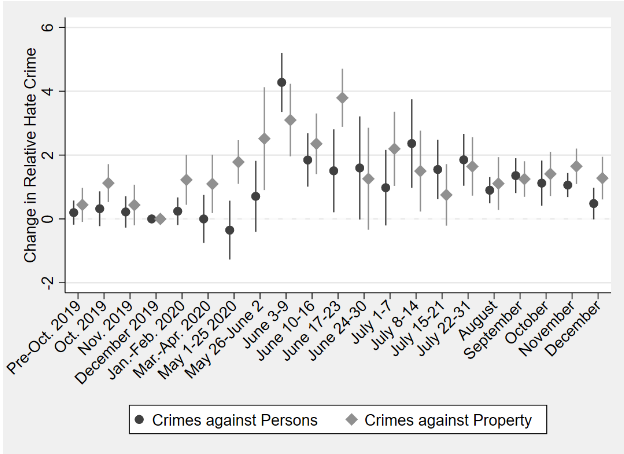
(d) Size: Anti-White HC

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). Regression population includes control groups of the baseline analyses: other groups and biases. These include racial hate crimes against Asians and Pacific Islanders, Native Americans/Alaskans, Hispanics, and Other racial groups, religious hate crimes against Christians, other religious groups, antisemitism, and Arab/Muslims, as well as disability, transgender, gender, and homophobic hate crime. Baseline period is December 2019. **Panels (a-b)**: Effect of protests by Census regions - North Central, Northeast, South, and West. **Panels (c-d)**: Effect of protests by size of the municipality where the crime was recorded based on FBI's categorization.

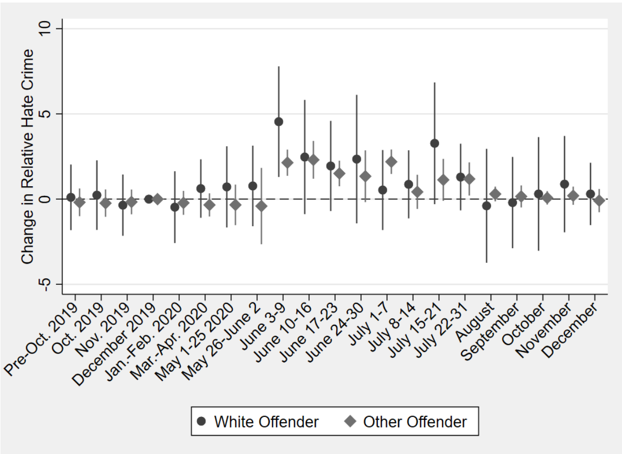
Figure 15: Results by Crime Characteristics, ES



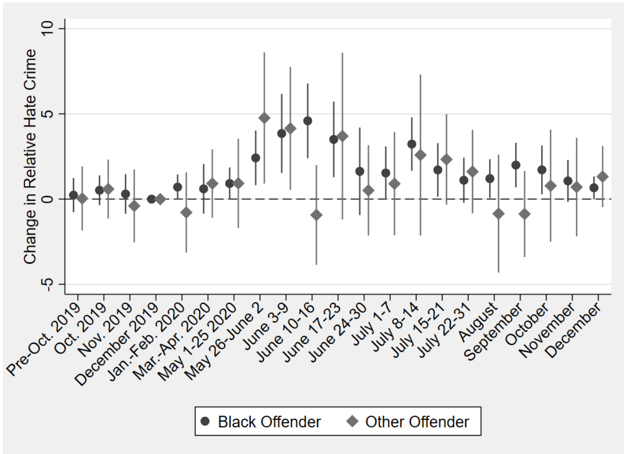
(a) Prop/Person: Anti-Black HC



(b) Prop/Person: Anti-White HC



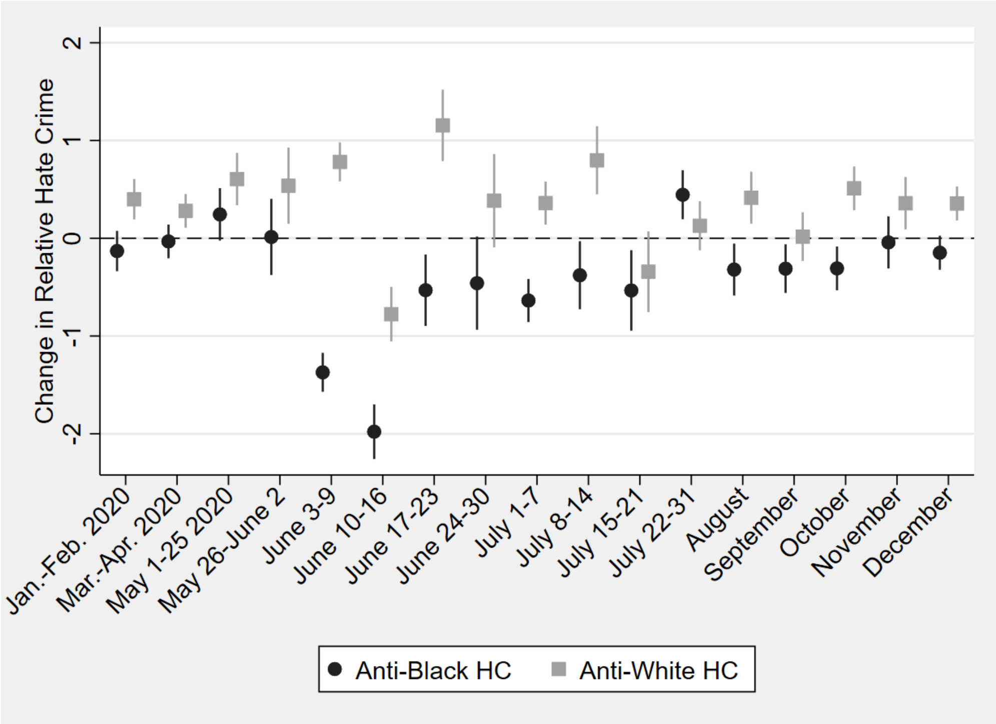
(c) Offender Race: Anti-Black HC



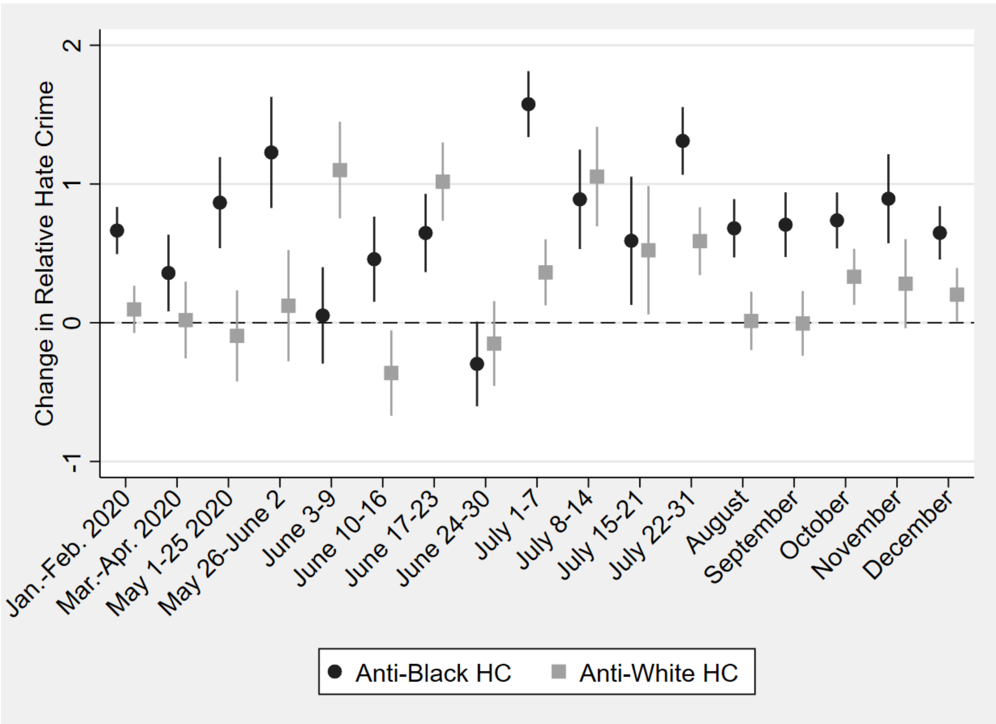
(d) Offender Race: Anti-White HC

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). Regression population includes control groups of the baseline analyses: other groups and biases. These include racial hate crimes against Asians and Pacific Islanders, Native Americans/Alaskans, Hispanics, and Other racial groups, religious hate crimes against Christians, other religious groups, antisemitism, and Arab/Muslims, as well as disability, transgender, gender, and homophobic hate crime. Baseline period is December 2019. **Panel (a)**: Changes in crime against the person compared to crime against property. **Panel (b)**: Changes in anti-Black and anti-White hate crime by race of the offender.

Figure 16: Results by Presidential Voting, ES



(a) Change in Trump Vote

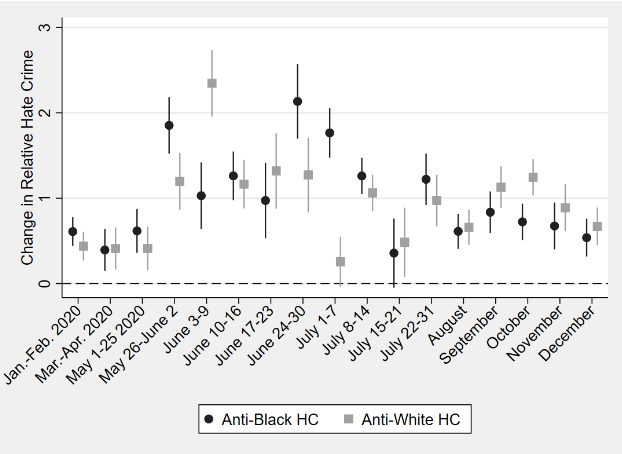


(b) 2016 Presidential Election

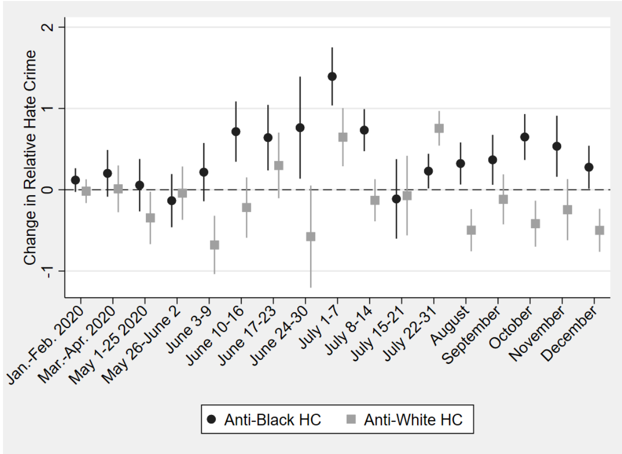
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). Regression population includes control groups of the baseline analyses: other groups and biases. These include racial hate crimes against Asians and Pacific Islanders, Native Americans/Alaskans, Hispanics, and Other racial groups, religious hate crimes against Christians, other religious groups, antisemitism, and Arab/Muslims, as well as disability, transgender, gender, and homophobic hate crime. Baseline period is December 2019. **Panel (a)**: Counties with an increase in votes share for Trump from 2016 to 2020 compared to those with a decrease. **Panel (b)**: Counties that voted for Hillary Clinton in 2016 compared to counties that voted for Trump.

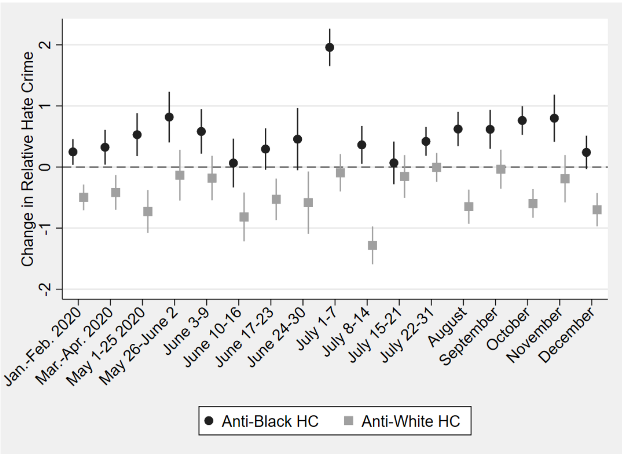
Figure 17: Results by County Demographics, ES



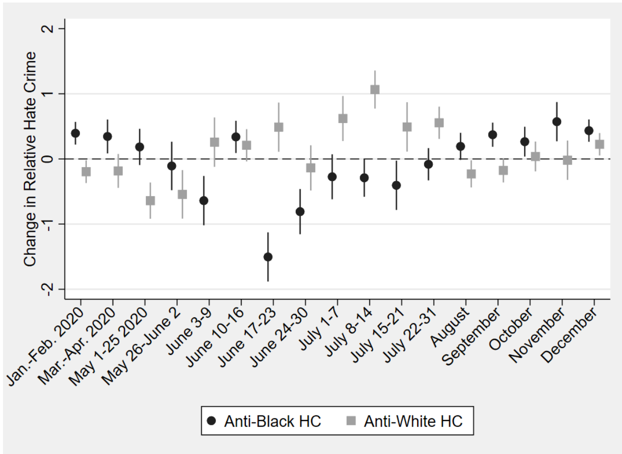
(a) Change in Unemployment



(b) Income



(c) College Degree

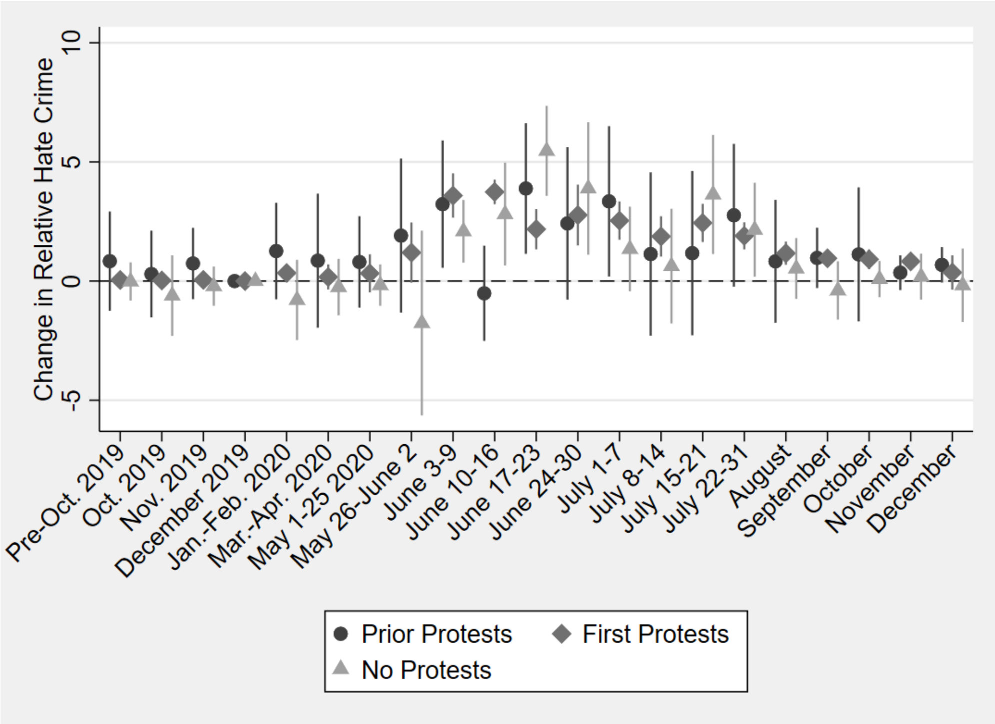


(d) Black Population

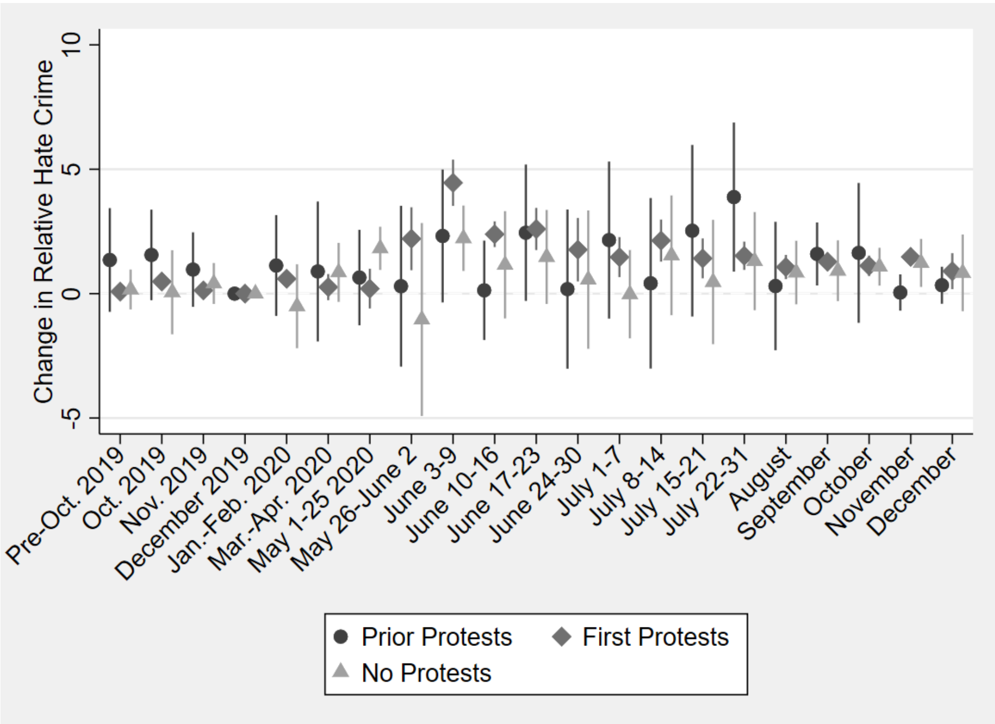
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). Regression population includes control groups of the baseline analyses: other groups and biases. These include racial hate crimes against Asians and Pacific Islanders, Native Americans/Alaskans, Hispanics, and Other racial groups, religious hate crimes against Christians, other religious groups, antisemitism, and Arab/Muslims, as well as disability, transgender, gender, and homophobic hate crime. Baseline period is December 2019. **Panel (a)**: Coefficients capture the difference between areas with higher than average changes in unemployment between 2019 and 2020 and areas with below average unemployment changes. **Panel (b)**: Coefficients capture the difference between areas with higher than average income and areas with below average income. **Panel (c)**: Coefficients capture the difference between areas with higher than average share of population with college degrees and areas with a below average share. **Panel (d)**: Coefficients capture the difference between areas with higher than average share of Black population and areas with a below average share.

Figure 18: Results by Protest Occurrance



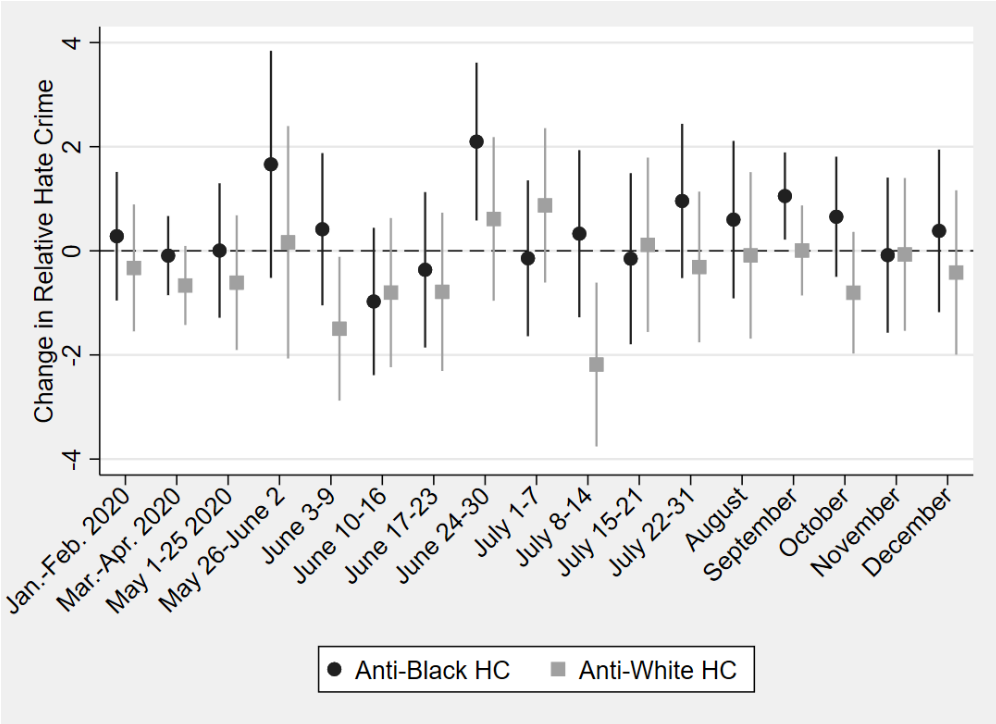
(a) Anti-Black HC



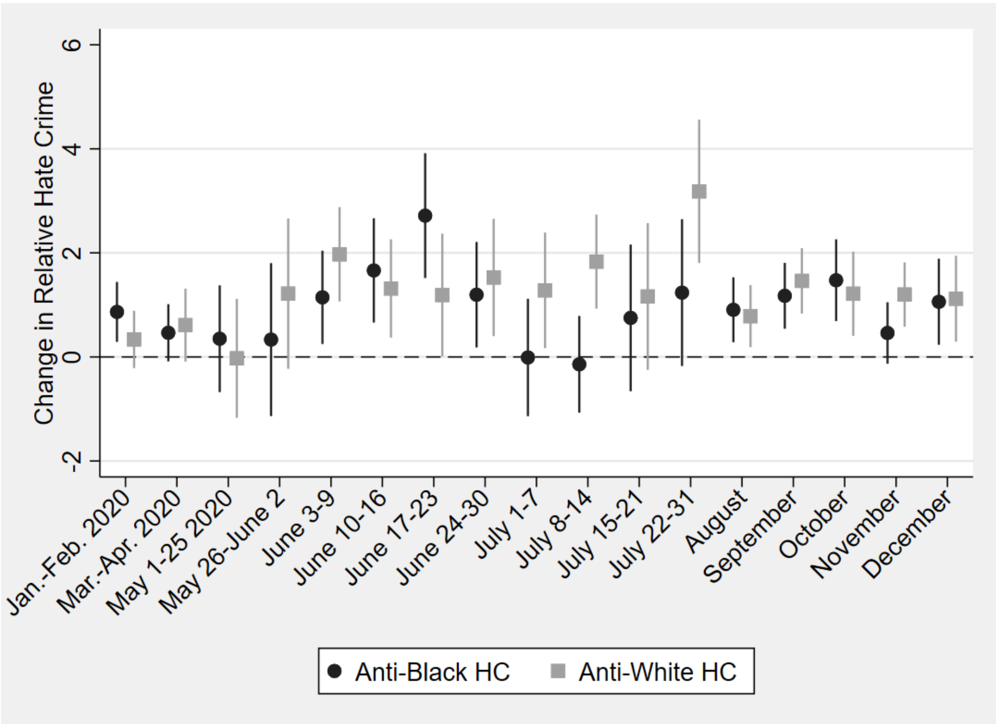
(b) Anti-White HC

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated group is anti-Black hate crime and the control groups are other groups and biases. The baseline period is December 2019. **Panel (a)**: coefficients measure difference between states with above and below average stringent COVID policies prior to protests. **Panel (b)**: coefficients measure the difference between states with above and below average economic support in 2020 prior to protests.

Figure 19: Results by Covid Policies



(a) Stringency

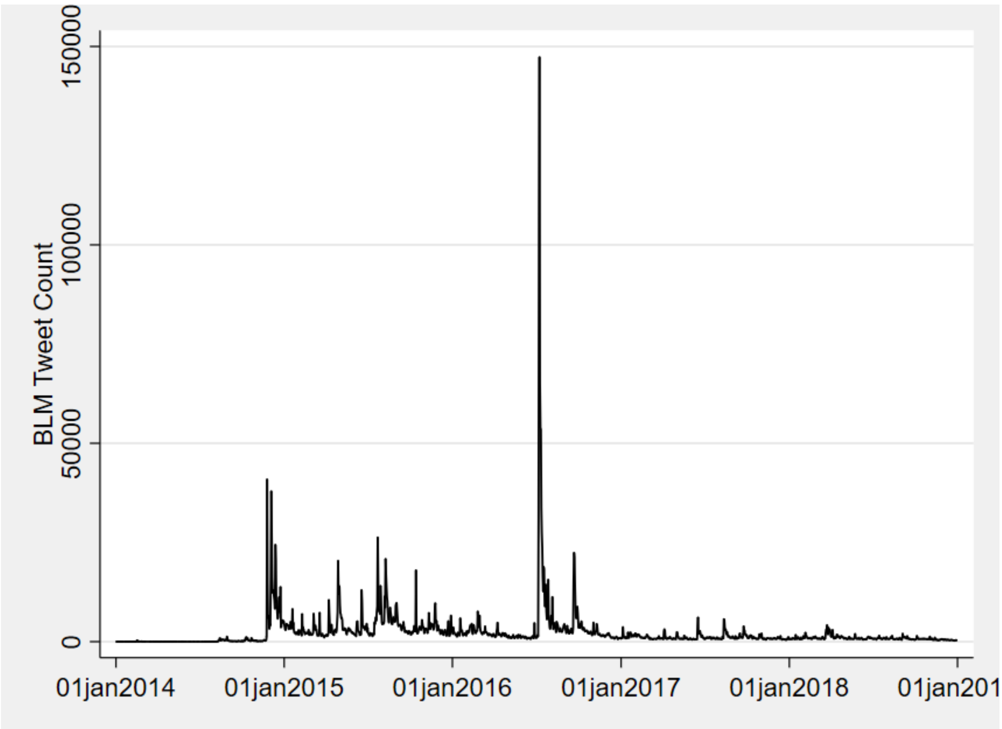


(b) Economic Support

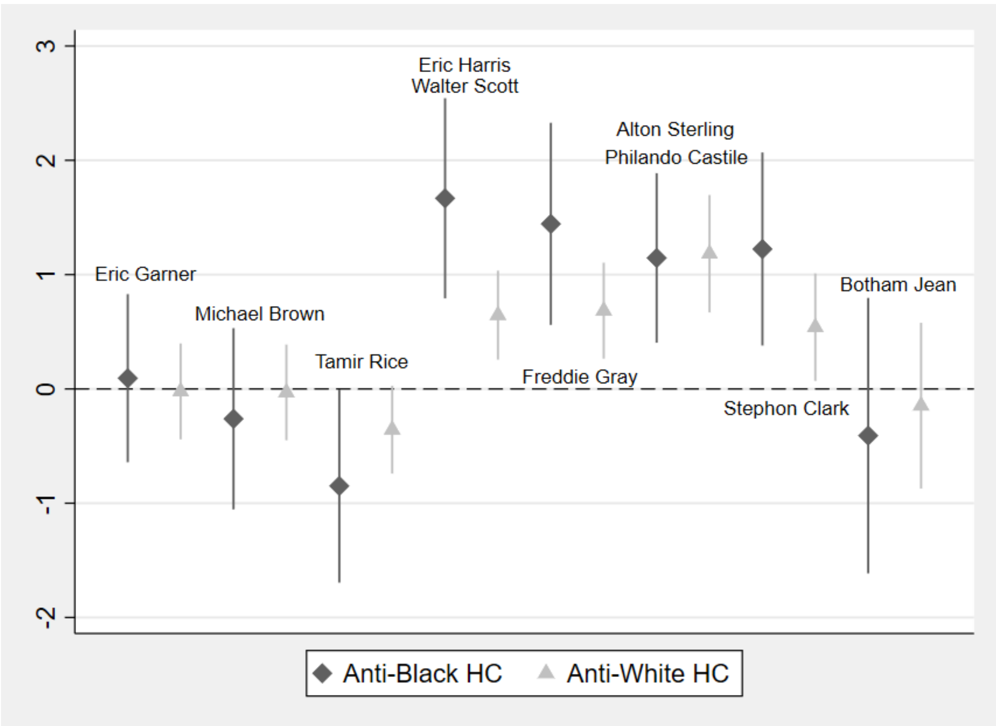
Source: Recorded crime data from the FBI's Uniform Crime Report.

Notes: Outcome variable is measured as deviation from the pre-treatment average relative to the average (percent deviation). The treated group is anti-Black hate crime and the control groups are other groups and biases. The matching period is May 2016 to December 2019.

Figure 20: Comparison to Other Salient Deaths, RD



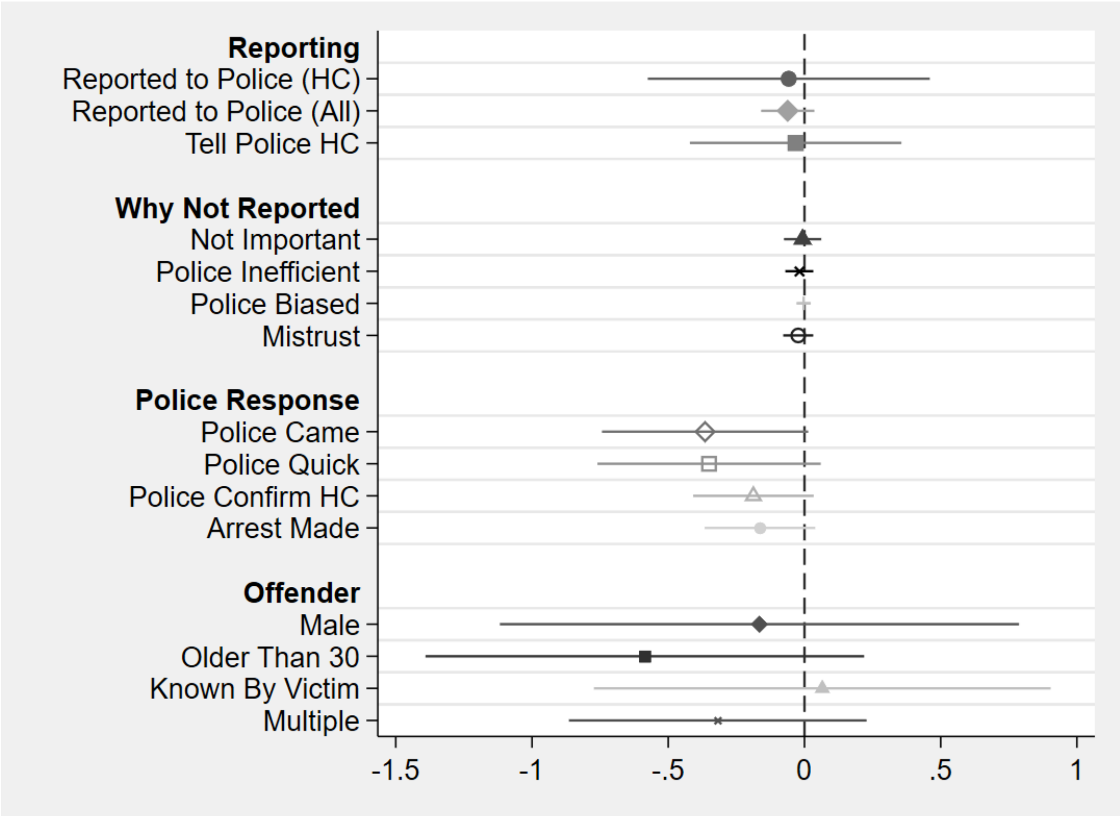
(a) BLM Tweet Count



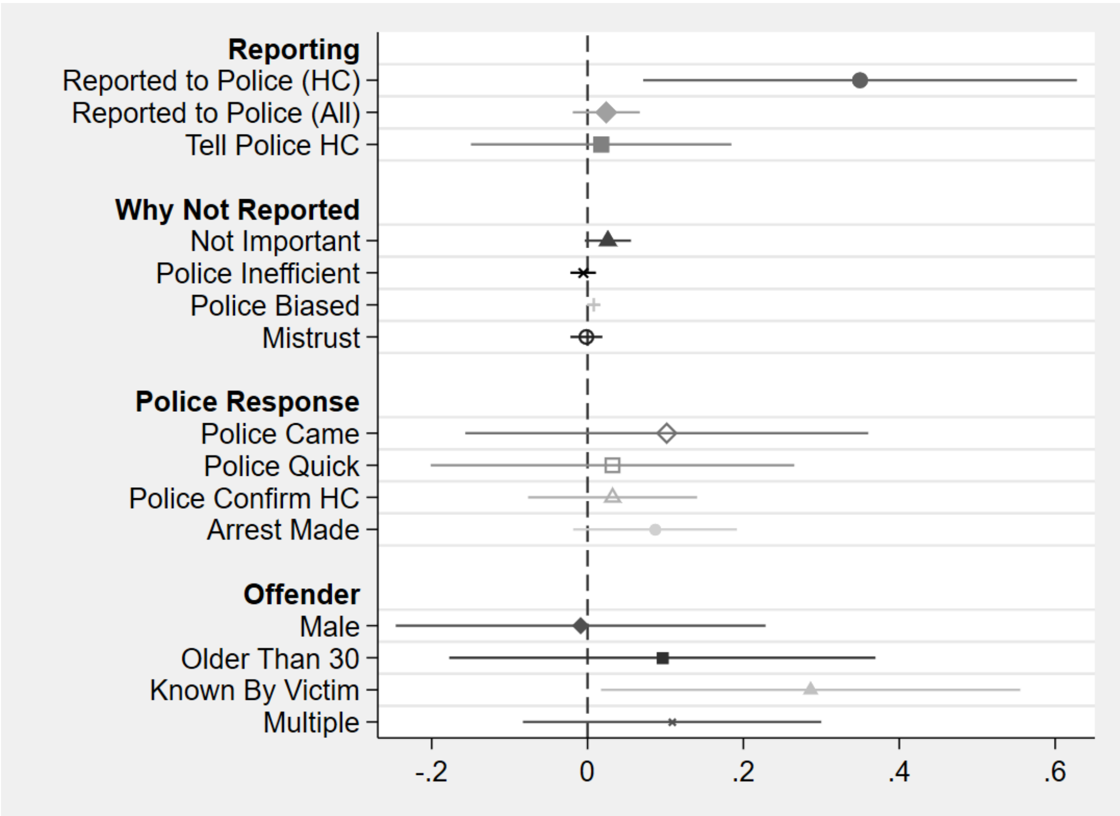
(b) Discontinuities

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is measured as crime count. For each the discontinuity begins the day following the (first) death. The dates of deaths are as follows: Eric Garner (July 17, 2014), Michael Brown (August 9, 2014), Tamir Rice (November 22, 2014), Eric Harris (April 2, 2015), Walter Scott (April 4, 2015), Freddie Gray (April 12, 2015), Alton Sterling (July 5, 2016), Philando Castile (July 6, 2016), Stephon Clark (March 18, 2018), and Botham Jean (September 6, 2018). For deaths in close proximity the date following the first death is used in a single estimation.

Figure 21: Crime Victimization Survey



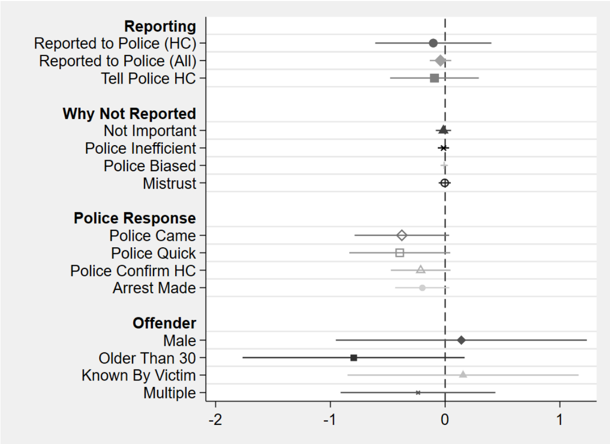
(a) Black Americans



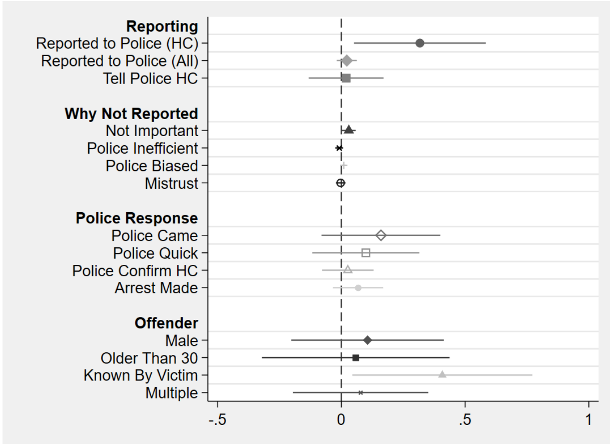
(b) White Americans

Source: Victimisation data from the National Crime Victimization Survey.
Notes: Regression discontinuity beginning at the protests with triangular kernel weighting applied. White Americans refer to non-Hispanic Caucasians by self-identification.

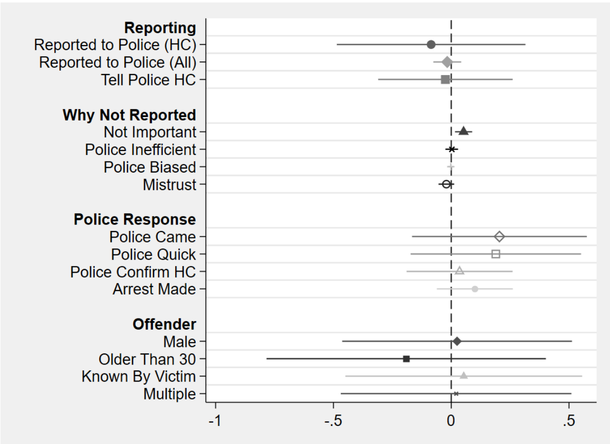
Figure 22: Crime Victimization Survey Robustness



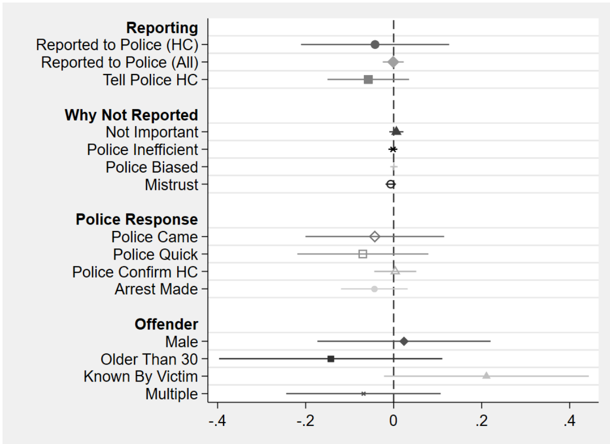
(a) Global: Black Americans



(b) Global: White Americans



(c) Placebo: Black Americans



(d) Placebo: White Americans

Source: National Crime Victimization Survey.

Notes: Regression discontinuity beginning at the protests with triangular kernel weighting applied. White Americans refer to non-Hispanic Caucasians by self-identification. **Panels (a-b)**: global quadratic regression discontinuity with inverse distance weighting. **Panels (c-d)**: Placebo in time at June 2019.

Table 1: Summary Statistics Table

	N	Mean	Std. dev.	Min	Max
Hate Crime Categories					
Arab/Muslim	4,018	0.650	0.898	0	6
Asian	4,018	0.429	0.719	0	11
Black	4,018	5.704	3.279	0	37
Gender	4,018	0.105	0.354	0	4
Native American	4,018	0.359	0.619	0	4
Orientation	4,018	3.299	1.988	0	12
Other Race	4,018	0.865	0.997	0	9
Christian	4,018	0.350	0.646	0	7
Other Religion	4,018	0.610	0.848	0	8
Transgender	4,018	0.296	0.614	0	6
White	4,018	1.922	1.558	0	16
Antisemitic	4,018	2.228	1.776	0	17
Disability	4,018	0.277	0.545	0	4
Hispanic	4,018	1.190	1.169	0	7
Multi-Racial	4,018	0.387	0.677	0	7
Media					
Other networks	1,827	5.138	15.717	0	128
CSPAN	1,827	1.423	2.794	0	19
CNN	1,827	0.750	2.442	0	25
FoxNews	1,827	1.534	4.101	0	27
MSNBC	1,827	0.851	2.469	0	21
Twitter	1,827	5687.140	40836.240	163	1219633
Tweets					
Blue Lives Matter	1,827	615.833	1669.750	0	47459
Chauvin	1,827	23.890	399.978	0	15932
All Lives Matter	1,827	658.316	3008.804	0	53344
Police Violence	1,827	0.653	3.121	0	52
Defund the Police	1,827	643.567	2930.114	0	57818
Statues	1,827	30.211	115.584	0	2074
BLM Protests	1,827	21.765	100.262	0	1442
Hate Crime	1,827	3.486	8.145	0	134
Unemployment	1,827	465.294	816.074	0	7975
Protest Data					
Count Protests	1,827	4.366	29.054	0	533
Count Protesters	1,827	960.587	10554.730	0	260060

Source: Recorded crime data from the FBI's Uniform Crime Report. TV headlines from archive.org. Tweets from author's own calculations. Protest data from Count Love (https://countlove.org/).

Table 2: SCM Effects and Weights, Anti-Black HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.278	0.429	Antisemitism	0.012
June 2020	2.590	0.000	Arab/Muslim	0.008
July 2020	1.425	0.000	Asian	0.013
August 2020	0.861	0.000	Disability	0.008
Sept. 2020	0.660	0.000	Gender	0.002
Oct. 2020	0.287	0.143	Hispanic	0.013
Nov. 2020	0.428	0.000	Homophobia	0.619
Dec. 2020	0.085	0.714	Nat. Amer.	0.021
			Race-Other	0.267
			Rel.-Christian	0.011
			Rel.-Other	0.025
			Transphobia	0.002

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment average (by hate crime type/group). Matching has been minimised for the four years prior to the treatment.

Table 3: SCM Effects and Weights, Anti-White HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.034	1.000	Antisemitism	0.067
June 2020	1.651	0.000	Arab/Muslim	0.046
July 2020	0.643	0.083	Disability	0.045
August 2020	0.369	0.333	Gender	0.013
Sept. 2020	0.757	0.083	Homophobia	0.266
Oct. 2020	0.244	0.500	Race-Asian	0.069
Nov. 2020	0.528	0.083	Race-Hispanic	0.069
			Race-Other	0.235
			Rel.-Christian	0.060
			Rel.-Other	0.065
			Transphobia	0.016

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment average (by hate crime type/group). Matching has been minimised for the four years prior to the treatment.

Table 4: SCM 3 Years: Effects and Weights, Anti-Black HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.358	0.357	Antisemitism	0.013
June 2020	2.673	0.000	Arab/Muslim	0.011
July 2020	1.564	0.000	Disability	0.006
August 2020	0.866	0.000	Gender	0.002
Sept. 2020	0.693	0.000	Homophobia	0.768
Oct. 2020	0.276	0.142	Race-Asian	0.011
Nov. 2020	0.414	0.000	Race-Hispanic	0.013
Dec. 2020	0.117	0.642	Race-Nat. Amer.	0.026
			Race-Other	0.109
			Rel.-Christian	0.027
			Rel.-Other	0.010
			Transphobia	0.003

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment average (by hate crime type/group). Matching has been minimised for the three years prior to the treatment.

Table 5: SCM No Homophobia: Effects and Weights, Anti-Black HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	-0.044	0.923	Antisemitism	0.012
June 2020	2.222	0.000	Arab/Muslim	0.008
July 2020	0.859	0.000	Disability	0.008
August 2020	0.838	0.000	Gender	0.001
Sept. 2020	0.524	0.462	Race-Asian	0.012
Oct. 2020	0.333	0.385	Race-Hispanic	0.012
Nov. 2020	0.483	0.308	Race-Nat. Amer	0.020
Dec. 2020	-0.038	0.846	Race-Other	0.892
			Rel.-Christian	0.023
			Rel.-Other	0.011
			Transphobia	0.002

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment average (by hate crime type/group). Homophobic hate crime is removed from the control basket.

Table 6: SCM Average: Effects and Weights, Anti-Black HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.267	1.000	Antisemitism	0.062
June 2020	5.749	0.000	Arab/Muslim	0.080
July 2020	3.717	0.000	Disability	0.083
August 2020	1.898	0.000	Gender	0.090
Sept. 2020	1.118	0.286	Homophobia	0.075
Oct. 2020	1.082	0.429	Race-Asian	0.087
Nov. 2020	0.728	0.357	Race-Hispanic	0.087
Dec. 2020	-0.321	0.571	Race-Nat. Amer.	0.088
			Race-Other	0.066
			Rel.-Christian	0.090
			Rel.-Other	0.092
			Transphobia	0.010

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment standard deviation (by hate crime type/group).

Table 7: SCM Placebo in Time: Effects and Weights, Anti-Black HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.034	1.000	Antisemitism	0.067
June 2020	1.651	0.000	Arab/Muslim	0.046
July 2020	0.643	0.083	Disability	0.045
August 2020	0.369	0.333	Gender	0.013
Sept. 2020	0.757	0.083	Homophobia	0.266
Oct. 2020	0.244	0.500	Race-Asian	0.069
Nov. 2020	0.528	0.083	Race-Hispanic	0.069
Dec. 2020	0.113	0.833	Race-Nat. Amer.	0.049
			Race-Other	0.235
			Rel.-Christian	0.060
			Rel.-Other	0.065
			Transphobia	0.016

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment standard deviation (by hate crime type/group).

Table 8: SCM 3 Years: Effects and Weights, Anti-White HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.191	0.833	Antisemitism	0.050
June 2020	1.830	0.000	Arab/Muslim	0.044
July 2020	0.769	0.000	Disability	0.025
August 2020	0.463	0.250	Gender	0.007
Sept. 2020	0.890	0.000	Homophobia	0.475
Oct. 2020	0.270	0.500	Race-Asian	0.043
Nov. 2020	0.608	0.000	Race-Hispanic	0.048
Dec. 2020	0.241	0.500	Race-Nat. Amer.	0.037
			Race-Other	0.179
			Rel.-Christian	0.040
			Rel.-Other	0.040
			Transgender	0.011

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment average (by hate crime type/group). Matching has been minimised for the three years prior to the treatment.

Table 9: SCM No Homophobia: Effects and Weights, Anti-White HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.034	1.000	Antisemitism	0.067
June 2020	1.651	0.000	Arab/Muslim	0.046
July 2020	0.643	0.083	Disability	0.045
August 2020	0.369	0.333	Gender	0.013
Sept. 2020	0.757	0.083	Homophobia	0.266
Oct. 2020	0.244	0.500	Race-Asian	0.069
Nov. 2020	0.528	0.083	Race-Hispanic	0.069
Dec. 2020	0.113	0.833	Race-Nat. Amer.	0.049
			Race-Other	0.235
			Rel.-Christian	0.060
			Rel.-Other	0.065
			Transgender	0.016

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment average (by hate crime type/group). Homophobic hate crime is removed from the control basket.

Table 10: SCM Average: Effects and Weights, Anti-White HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2020	0.442	0.917	Antisemitism	0.108
June 2020	4.672	0.000	Arab/Muslim	0.077
July 2020	2.038	0.000	Disability	0.070
August 2020	1.072	0.167	Gender	0.050
Sept. 2020	2.115	0.000	Homophobia	0.178
Oct. 2020	0.774	0.667	Race-Asian	0.062
Nov. 2020	1.406	0.083	Race-Hispanic	0.087
Dec. 2020	0.387	0.583	Race-Nat. Amer.	0.071
			Race-Other	0.092
			Rel.-Christian	0.078
			Rel.-Other	0.071
			Transgender	0.057

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment standard deviation (by hate crime type/group).

Table 11: SCM Placebo in Time: Effects and Weights, Anti-White HC

Treatment Effects			Synthetic Weights	
	Treatment	P-values	Group	Weight
May 2019	-0.081	0.583	Antisemitism	0.088
June 2019	-0.452	0.333	Arab/Muslim	0.060
July 2019	-0.403	0.083	Disability	0.068
August 2019	-0.171	0.667	Gender	0.047
Sept. 2019	-0.312	0.250	Homophobia	0.115
Oct. 2019	-0.093	0.583	Race-Asian	0.133
Nov. 2019	-0.383	0.083	Race-Hispanic	0.087
Dec. 2019	-0.624	0.000	Race-Nat. Amer.	0.054
			Race-Other	0.126
			Rel.-Christian	0.077
			Rel.-Other	0.093
			Transgender	0.051

Source: Recorded crime data from the FBI's Uniform Crime Report.
Notes: Outcome variable is defined as the crime count divided by the pre-treatment standard deviation (by hate crime type/group).