HIGH TIMES FOR HATE CRIMES:
EXPLAINING THE TEMPORAL CLUSTERING
OF HATE-MOTIVATED OFFENDING*

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This research explains the temporal clustering of hate crimes. It is hypothesized that many hate crimes are retaliatory in nature and tend to increase, sometimes dramatically, in the aftermath of an antecedent event that results in one group harboring a grievance against another. Three types of events are used to test and refine the argument: 1) contentious criminal trials involving interracial crimes, 2) lethal terrorist attacks, and 3) appellate court decisions concerning same-sex marriage. The results from time-series analyses indicate that contentious trial verdicts and lethal domestic terrorist attacks precede spikes in racially or religiously motivated hate crimes, whereas less evidence is found for anti-gay hate crimes after appellate court rulings that grant rights to same-sex partners. The model put forth in this article complements prior work by explaining in part the timing of hate crime clusters.

The study of hate crime sits at the intersection of two areas with a rich history in the social sciences—prejudice and criminal behavior. As such,

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empirical work in this domain has been generally informed by theories of
crime and prejudice, such as social disorganization theory in criminology
(Lyons, 2007) and the influential ideas of Blalock (1967), Horwitz (1985),
and Suttles (1972) in the study of discrimination and intergroup conflict (see
Green, Strolovitch, and Wong, 1998; Lyons, 2007). Although these distinct
literatures have generated unique hypotheses with respect to hate crime,
each has emphasized the importance of place (e.g., neighborhoods) and
has pointed to demographic composition or economic conditions as key ex-
planatory factors. We argue that this body of work on where hate crimes
occur is not balanced by research on when they happen, and we find it curi-
ous that prior work has focused almost exclusively on demographic factors
and economic conditions as determinants of offending while giving scant
attention to the importance of discrete events that could ignite a wave of
hate crime. As one illustration of the power of singular events, consider the
case of anti-Muslim hate crimes after the 9/11 terrorist attacks. According
to U.S. Federal Bureau of Investigation (FBI) statistics, 481 hate crimes
occurred with a specific anti-Islamic motive that year, with an incredible
279 of them perpetrated during a 2-week period beginning on September
11, 2001—that is, 58 percent of crimes in less than 4 percent of the at-risk
period. It seems clear that the wave of hate crime was in response to the
9/11 terrorist attacks rather than in response to any economic calamity or
demographic shift (Disha, Cavendish, and King, 2011), and we think the
post-9/11 spike in hate crimes calls for a more thorough examination of the
role of discrete events. This suggestion is bolstered by research showing
that both crime and prejudice are influenced in the short term by singular
events such as widely publicized murders (Phillips, 1980, on homicide), riots
(Bobo et al., 1994, on race relations), and terrorism (Legewie, 2013, on anti-
immigrant sentiment). Our objective in this investigation is to propose and
test an explanation of hate crime that emphasizes the temporal proximity
of these crimes in relation to discrete antecedent events. Specifically, does
an association exist between hate crime and widely publicized events that
generate anger and intergroup hostility? And under what conditions might
we expect hate crimes to increase after an antecedent event?

Our inquiry is guided by three lines of theory and research. First, prior
work has indicated that hate crimes often are defensive in nature and are
precipitated by an affront to one demographic group by another (Lyons,
2007). In essence, they are partly an expression of informal social control,
and thus, we draw on theories in sociology (Black, 1983) and psychology
(Lickel et al., 2006) that perceive crime as reactionary and retributive. But
what causes this desire for retribution? Research on the politics of vio-
ence has indicated that crimes entailing a prejudicial motive often occur
in close temporal proximity to galvanizing events, such as elections. For in-
stance, anti-Semitic violence in pre–World War II Germany increased when
leftist parties did well in elections (King and Brustein, 2006). In this work, we make a related argument for the case of hate crimes, although we examine events outside the political realm. Third, our methodological approach resembles the work of Phillips (1974, 1979, 1980, 1983), who examined daily variation in suicides and homicides in relation to other widely publicized violent episodes. For example, Phillips (1983) found that homicides increased in the days after highly touted prize fights. Our theoretical perspective differs from his work, yet the methodological approach of Phillips demonstrated the utility of looking at discrete events to understand crime and violence. In the current work, we refer to events such as those mined by Phillips as *antecedent events* (or “triggering events”) and we investigate whether they help explain temporal variation in hate crime.

We proceed first by reviewing key theoretical concepts that guide our inquiry. We then describe the data, identify antecedent events, and explain our analytic strategy before turning to the results, which indicate that hate crimes often cluster in time and escalate in close temporal proximity to events that stir intergroup conflict, and leave one group with a grievance against another, such as contentious interracial trials and lethal terrorist attacks.

**RETRIBUTION, VICARIOUSNESS, AND ANTECEDENT EVENTS**

**CRIME AS VICARIOUS RETRIBUTION**

Black’s (1983) theory of crime as social control provides a theoretical foundation for our explanation of hate crime. Black posited that many crimes can be thought of as forms of “self-help”—“the expression of a grievance by unilateral aggression such as personal violence or property destruction” (1983: 34). In short, criminal behavior sometimes satisfies a desire for justice, particularly among those who cannot easily turn to law enforcement for help. Black further suggested that some crimes amount to forms of collective liability in which innocents are attacked simply because they belong to a particular group. For example, “a police officer might become the victim of a surprise attack by a stranger . . . because of the conduct of one or more fellow officers in the past” (Black, 1983: 38), a proposition that resonates with what gang researchers call “generalized violence” (Pappachristos, 2009: 81).

This idea of collective liability aligns with the concept of vicarious retribution put forth in the social psychology of aggression (Lickel et al., 2006). Vicarious retribution occurs when “a member of a group commits an act of aggression toward members of an out-group for an assault or provocation that had no personal consequences for him or her, but did harm a fellow
in-group member” (Lickel et al., 2006: 372–3)—in other words, when a member of group A is aggressive toward an innocent member of group B for the actions of a third party who also belonged to group B.

In their discussion of vicarious retribution, Lickel et al. (2006) also drew explicit attention to the role of provocation, particularly discrete events that stoke a sense of group pride in the victimized group, which in turn can incite retribution that is vicarious in nature. As previously mentioned in this article and by Lickel et al., the case of post-9/11 hate crimes is an exemplar of this phenomenon. A violent act was perpetrated, a definable out-group was identified immediately thereafter, the emotion of anger was thick and widespread in American society after the attacks, justice through legal channels would be impossible because of the suicidal nature of the attack, and hate crimes against innocent third parties followed. To the extent that these factors are not unique to 9/11, we might then understand some crime and aggression as retributive, moralistic, and aimed at innocent third parties. These circumstances are particularly helpful for understanding hate crimes, which are inherently moralistic because by definition they entail a degree of prejudice or hatred against the victim’s group.

RETRIBUTION AND ANTECEDENT EVENTS

In addition to explaining the motivation for some crimes, Black (1983) also explained who is more likely to resort to self-help. He posited that people with less access to law—namely, the lower class or those living in “stateless” (p. 41) or lawless places in modern society—are prone to retribution through illicit acts.

A similar mentality is at the heart of the current argument. Hate crimes often are perpetrated because offenders have a grievance against another group of a different race, ethnicity, religion, sexual orientation, or other characteristic (Craig, 1999). Consistent with Black’s (1983) thesis, we suggest that hate crimes are more likely when the group harboring the grievance cannot turn to the law to rectify the conflict or otherwise find closure. We might think of hate crimes as motivated in part by a temporary sense of legal cynicism (Kirk and Papachristos, 2011; Sampson and Bartusch, 1998) in which circumstances of an event seem to preclude the possibility of justice through legal channels. For instance, after a suicide terrorist attack, there is no criminal justice for the perpetrators, and after an acquittal in a controversial trial laden with racial or religious overtones, double jeopardy precludes a retrial. Even if perpetrators do not reside in “stateless” societies as Black (1983) suggested, they may feel there is no legal channel through which to deal with a grievance.

We also emphasize a few ways in which our work departs from Black’s (1983) theory. First, we suggest that beliefs about the law and its
capacity for meting out justice crosses racial and class lines, a point that de-
parts from Black’s theorizing but partly agrees with a related line of work on
legal cynicism.¹ For instance, we suggest that triggering events may ignite
waves of anti-White or anti-Black hate crimes, depending on the nature of
the grievance. Second, Black’s work on self-help predicts which groups are
more apt to engage in moralistic crime, although his theory is not specific
about the timing. The work of Lickel et al. (2006) takes us a step closer by
highlighting the role of provocation and conditions under which provoca-
tion might be pacified or escalate to aggression. However, their work leaves
open a critical question: What types of events ignite intergroup conflict?

Prior work on prejudice and intergroup violence has suggested that
abrupt changes in the political environment and acts of violence can serve
as triggers. For example, the murderous Kristallnacht pogrom of 1938 fol-
lowed an antecedent event—the assassination of a German diplomat at the
hands of a Jewish youth (Brustein, 2003)—and previous anti-Jewish vio-
lence increased when political parties with strong Jewish representation did
well in elections (King and Brustein, 2006). In the United States, lynch-
ing in the South often increased when social movements vying to grant
civil rights to Blacks were successful (Olzak, 1990), and more recent work has
found that cities with Black mayors have more White-on-Black killings
(Jacobs and Wood, 1999). Interrupted time-series analyses in the study of
anti-immigrant sentiment also has suggested that events such as lethal ter-
rorist attacks ignite antipathy toward immigrants, at least in the short term
(Hopkins, 2010; Legewie, 2013). These examples are taken from various
times and places and focus on different outcome variables; yet a common
thread is that attitudes toward outgroups and intergroup violence increased
in response to events (e.g., elections and terrorism) occurring in close tem-
poral proximity that left one group with a sense of hostility or even a desire
for vengeance against a definable outgroup.

We identify contemporary events that also might stoke anger or repre-
sent an affront to another group. For example, terrorist attacks can trig-
ger anger and prejudice and can ignite a backlash by the victimized group
against individuals who resemble the alleged perpetrators, as evidenced
by public opinion about and hate crimes against Arabs and Muslims af-
fer 9/11 (Disha, Cavendish, and King, 2011; Gallup, 2009) or against im-
migrants in Europe after terrorist attacks (Legewie, 2013). We also might
consider the aftermath of contentious criminal trials. Kennedy (1998: 302),
for instance, noted how the acquittal of O.J. Simpson induced a backlash

¹. As Sampson and Bartusch (1998: 800) stated in their pioneering work on legal cyn-
icism, “if there is a subcultural system that tolerates deviance and turns a cynical
eye toward the law . . . it is not linked in a simple way to race.”
among many Whites. Finally, new rights and privileges conferred on historically marginalized groups can prompt a backlash (Manza and Uggen, 2006), although no research has investigated the association between hate crimes and legislation or appellate court decisions. To this end, we ask whether appellate court decisions mandating equal treatment of same-sex partners causes a spike in antigay hate crime. In sum, we examine empirically whether prejudicial acts such as hate crimes increase after terrorist attacks, contentious and racially charged criminal trials, and court decisions conferring rights on historically marginalized groups.

**THIS STUDY**

The theory and research discussed earlier in tandem with prior work on the aftermath of terrorist attacks in the United States (Disha, Cavendish, and King, 2011) and Europe (Legewie, 2013) offered concepts that help explain temporal variation in hate crime. Five points are particularly instructive, and we summarize them here before moving to the analysis.

First, it seems that sharp increases in crimes motivated by prejudice, be they hate crimes after 9/11 or anti-Jewish pogroms after an assassination in pre–World War II Germany, often are reactive in nature and precipitated by an *antecedent event*. Second, the antecedent event matters when a *clearly definable group* is associated with the initial triggering act, such as Muslims in the case of 9/11. An implication is that groups with a grievance could clearly identify people who at least looked like those implicated in the triggering act. Third, antecedent events spark a reaction when they generate *considerable publicity*, thus making the details of the event known to a broad public. Fourth, prior work on the aftermath of terrorism has indicated that reactions by the public are generally intense but *short in duration* (Disha, Cavendish, and King, 2011; Legewie, 2013). Fifth, the reactive hate crimes seem *vicarious* in nature. Innocent Jews were victimized during the *Kristallnacht* pogrom and innocent Muslims, Sikhs, and Arabs after 9/11. In the latter case, hate crimes also were dispersed across the country, including many cities not directly impacted by the attacks.

Building on the illustrative cases such as *Kristallnacht* and 9/11, along with theoretical work on social control, vicarious retribution, and political violence, we suggest that hate crimes are likely to increase, sometimes dramatically, in the wake of antecedent events with these characteristics. This argument is examined empirically using available hate crime data in the United States with a focus on three types of antecedent events: widely publicized contentious trial verdicts after interracial crimes, lethal domestic terrorist attacks, and the aftermath of appellate court decisions granting rights to historically marginalized groups.
Hate crime data come from the annual Uniform Crime Reports (UCR) Program. After the passage and implementation of the Hate Crimes Statistics Act of 1990 (HCSA), local law enforcement agencies have been asked to submit reports of hate crimes within their jurisdictions to be included in the annual UCR. The data are useful for our purposes, but we acknowledge that undercounting of hate crime incidents has been a persistent problem and that reporting practices are correlated with the demographic and political characteristics of counties and cities (King, 2007; King, Messner, and Baller, 2010; McVeigh, Welch, and Bjarnason, 2003). We also acknowledge the possibility that victims of hate crimes may be more apt to report them after events such as terrorism, although it is equally plausible that police may share the same prejudices as some members of the public after an event (e.g., lethal terrorism) and thus be disinclined to report incidents. The reporting issue cannot be untangled empirically with available data, and as such we try to minimize the problem by also analyzing a subset of data that includes only reports from law enforcement agencies that had complied with the HCSA before and after the event in question, thus holding the reporting tendencies of the police department constant. We also note that the undercount problem is balanced by some unique and useful features of the hate crime data. For instance, the data include information about the type of bias displayed during the offense, along with the date and location. Such information is useful for this analysis because we are interested primarily in the timing of offending in relation to other events occurring in close temporal proximity.

We examine temporal variation in hate crimes in relation to three types of antecedent events. First, we assess the association between hate crimes and contentious trials by examining hate crimes after two acrimonious cases: the acquittal of the White officers charged with the violent beating of Rodney King, an African American, and the acquittal of O.J. Simpson, an African American charged with a double homicide involving two White victims. We chose these cases because they were widely publicized interracial violent events that resulted in formal charges, trials, and ultimately acquittals that left many members of a racial group feeling cynical and aggrieved. We then referenced two additional sources in search of other high-profile cases that entailed an intergroup offense and resulted in an acquittal. First, Linder (2012) tracked famous trials in American history and identified six that occurred during our time period of interest (post-1992, when hate crime data are first available); yet only the King and Simpson trials fit our criteria.\(^2\)

\(^2\) The other four famous trials identified by Linder are Ruby Ridge, Timothy McVeigh, Bill Clinton’s impeachment, and the Zacarias Massaoui trial. These
We then consulted Bailey and Chermak’s (2004: v.5) compilation of famous crimes and trials (post-1980), and again only the King and Simpson trials fit our criteria.

Two additional points about the analysis of hate crimes after these trials warrant mention. First, given the rarity of such cases, we use the King and Simpson cases largely for illustrative purposes, although we apply formal statistical tests to assess whether hate crime increased after these events. Second, and related, events such as these might be rare, but they can still have a sizeable effect on levels of hate crime.

The second stage of our analysis examines a longer time frame and focuses on anti-Arab and anti-Islamic hate crimes after terrorist attacks that 1) resulted in casualties and 2) for which Islamic fundamentalists were suspected of having perpetrated the attack \textit{in the immediate aftermath of the attack}. By “immediate aftermath,” we refer to a period of about 24 hours, which is enough time for an initial news cycle. To identify lethal terrorist attacks on the U.S. homeland, we consulted the Global Terrorism Database (LaFree, 2010) for the years 1992–2010. For each lethal attack, we then examined the \textit{New York Times} reporting on the event the next day to assess whether Islamic or Arab groups were suspected as perpetrators. This resulted in four attacks that fit our criteria: the 1993 attack on the World Trade Center; the Oklahoma City bombing, which initially was thought to be perpetrated by Islamic Fundamentalists\footnote{The \textit{New York Times} reported the following on April 20, 1995 (the morning after the attack): “Some experts focused on the possibility that the attack had been the work of Islamic militants, like those who bombed the World Trade Center in February 1993. … Some Middle Eastern groups have held meetings there, and the city is home to at least three mosques. … Several news organizations, including CNN, reported that investigators were seeking to question several men described as being Middle-Eastern in appearance who had driven away from the building” (Johnston, 1995: A1, B8).}; the 9/11 terrorist attacks, which we include as a single event; and the 2009 Fort Hood attack that left 13 dead after being shot by Nidal Malik Hasan.\footnote{The FBI hate crime data include a specific category for anti-Islamic hate crimes. We follow Disha, Cavendish, and King (2011: 28–30) and assume the “other-ethnicity” category almost entirely captures anti-Arab hate crimes. As Disha, Cavendish, and King made clear, this assumption is safe given that 1) nearly all other major ethnicities are specifically enumerated and 2) the anti-other hate crimes are highly correlated with anti-Muslim crimes over time. Indeed, the Pearson correlation (by day) between “anti-other ethnicity” and anti-Islamic hate crimes for the period 1992–2010 is .79.}

Finally, we assess whether laws conferring rights or privileges on minority groups incite a backlash in the form of hate crime. We do so with a...
descriptive analysis of hate crimes against gays after a landmark Vermont Supreme Court decision and then a more rigorous statistical test of Massachusetts after a similar court ruling. On December 20, 1999, the Vermont Supreme Court unanimously ruled that same-sex couples were entitled to the same benefits and protections afforded by Vermont law to married heterosexual couples, and the state congress was instructed to change state law to accommodate this entitlement. In late 2003, the Massachusetts Supreme Court issued a similar ruling with comparable instructions to the state congress. Thus, we examine whether antigay hate crimes changed after the respective court decisions.

ANALYTIC STRATEGY AND ESTIMATION

We summarize the analytic strategy for each of our cases in the next subsections, and we refer to supplementary analyses when reporting the results (see the online supporting information5). Also, models are expressed algebraically in the online supporting information (see equations S.1 and S.2).

CONTENTIOUS COURT CASES

We are interested first in whether hate crimes against Whites and Blacks increased immediately after the Rodney King and O.J. Simpson verdicts, respectively. For each case, we analyze data for the entire calendar year in which the verdict was given: 1992 for anti-White hate crimes after the trial of the officers charged with beating Rodney King (“King verdict” hereafter; \( N = 366 \) days) and 1995 for anti-Black hate crimes after the Simpson trial (\( N = 365 \) days). This is essentially an interrupted time-series analysis in which we assess whether hate crimes of a particular type increase, at least for a short time, after an antecedent event. We anticipate an immediate increase in hate crimes after each event followed by a fast rate of decay, which also is known as a “pulse function” (McDowall et al., 1980: 80). We capture the immediate aftermath of the verdict with a postverdict dummy variable, which constitutes our treatment period. Importantly, in consecutive models, we increase the duration of the postverdict period, beginning with 4 days, then 6, and then 8. We expect a significant and positive coefficient for the postevent dummy variable that captures the 4 days after the verdict, and if there is indeed a pulse function, then the coefficient should weaken as we increase the duration of the treatment period in subsequent models.

5. Additional supporting information can be found in the listing for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2011.51.issue-4/issuetoc.
TERRORISM

Our analytic strategy for the case of anti-Arab and anti-Muslim hate crimes after lethal terrorist attacks differs slightly from the analysis of the trials. Here, we have four events spanning nearly two decades rather than a single event in a single year. We thus include a dummy variable indicating that a lethal terrorist attack occurred on a given day along with lagged measures of this variable. The lagged variables allow us to test whether any correlation between terrorist attacks and anti-Arab and anti-Muslim hate crimes dissipates over time, and at what point a postevent increase in hate crimes (if any) returns to preevent levels.6

SAME-SEX MARRIAGE LAWS

We also examine changes in antigay hate crimes after court cases that grant new privileges to gays. We first provide a descriptive analysis of antigay hate crimes after the Baker v. Vermont (1999) Vermont Supreme Court decision, the first appellate court to rule that same-sex couples must receive benefits and be recognized by the state (see earlier discussion). Yet Vermont is a small state with few hate crimes reported in any given year, and as such, it is not well suited for a quantitative analysis. We thus include a second analysis using a more traditional time-series model for Massachusetts, which had a similar landmark state supreme court decision in 2003 (Goodridge v. Department of Public Health). Our strategy is similar to that described for the contentious trial verdicts in that we include dummy variables to capture the immediate postevent period and to assess decay.

CONTROL VARIABLES AND MODELING

Time-series analysis warrants attention to several issues. One is seasonality, which refers to cyclical behavior in a time series. Hate crimes, like other types of crime, are more frequent on weekends and during summer months. All models thus include dummy variables capturing day of the week and month of the year, with Sunday and December omitted as the respective reference categories. In addition, to help identify the effect of antecedent events on specific types of hate crimes (e.g., antigay crimes), we control for other types of hate crime as a proxy for unobserved factors that might affect hate crime reporting more broadly. For instance, when modeling anti-White hate crime as an outcome, we control for anti-Black hate crimes on the right side of the equation, and vice versa.

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6. For instance, a lag of 7 days indicates the effect of a lethal terrorist attack on hate crimes 7 days later. We show 0- through 10-day lags in the models and report on additional analyses using longer lags in the text.
A second concern is nonstationarity, a condition in which statistical parameters are not independent of time. A nonstationary process increases the chance of heteroskedasticity and of falsely rejecting a null hypothesis because a variable may trend in a particular direction around the time of an antecedent event without the event truly causing the change. A set of Dickey–Fuller tests for each analysis described earlier indicated trend stationary processes, and hence, we follow Raffalovich (1994) and detrend the data by controlling for linear time. Finally, time-series data are prone to serial correlation, which refers to the correlation between values of a time series and prior values of the same series. Scatterplots of contemporaneous and lagged values of the outcome variables and a series of Durbin–Watson tests indicates persistence (positive autocorrelation) in the time series for only one analysis—the case of anti-Islamic and anti-Arab hate crimes when including the year 2001—although no serial correlation was detected for the analysis of anti-White, anti-Black, or antigay hate crimes.\footnote{7}

We estimate the association between antecedent events and hate crimes using a negative binomial regression estimator with robust standard errors. This estimator is appropriate when analyzing non-negative integers in which overdispersion is present—as is the case with hate crime—and these models produced results that were substantively identical to generalized linear models. In addition, the results presented in the text were replicated in supplementary analyses using other strategies and specifications of the error structure, such as autoregressive Poisson models (see the online supporting information). The raw data and Stata code used in this article are available from the first author upon request.

RESULTS

TRIALS

We first consider the case of anti-White hate crimes after the King verdict on April 29, 1992. Models 1 through 3 in table 1 show the negative binomial coefficients with robust standard errors. The estimates in model 1 indicate that few of the control variables are significantly associated with anti-White hate crimes in 1992. Anti-Black and anti-White hate crimes are significantly correlated over time ($b = .052$), but the model detects no monthly or daily cyclical activity for anti-White hate crimes. Turning to the effect of the King verdict, the parameter indicating the 4-day period after the verdict is

\footnote{7. To generate Durbin–Watson statistics for each model, we first estimated an ordinary least-squares (OLS) model in Stata 12.1 (StataCorp, College Station, TX). We then used the postestimation commands to generate Durbin–Watson statistics at various lags.}
Table 1. Negative Binomial Estimates: Hate Crimes on Predictor Variables

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<td>−.226</td>
</tr>
<tr>
<td></td>
<td>(1.407)</td>
<td>(1.477)</td>
</tr>
<tr>
<td>N</td>
<td>366</td>
<td>366</td>
</tr>
<tr>
<td>Wald chi-square</td>
<td>238.72***</td>
<td>358.95***</td>
</tr>
<tr>
<td>(D.f.)</td>
<td>(20)</td>
<td>(20)</td>
</tr>
</tbody>
</table>

**NOTE:** Standard errors are in parentheses.

*p < .05; **p < .01; ***p < .001.
statistically significant ($b = 1.711$), which suggests a higher level of anti-White hate crimes perpetrated in the immediate aftermath of the King verdict. Models 2 and 3 extend the “treatment period” by 2 days each, and the results indicate a weaker but still statistically significant increase in anti-White hate crimes 6 and 8 days after the verdict, with an 18 percent reduction in the magnitude of the coefficient from the 4th to 8th day after the event, indicating a fairly fast rate of decay. Figure 1 shows the daily count of anti-White hate crimes during the year 1992 (black line) along with the preevent average (gray line). Not until approximately June do we observe a return to preevent levels, which suggests a sharp postverdict spike that decayed rapidly but nonetheless lingered for several weeks.

We next turn to anti-Black hate crimes in 1995 after the O.J. Simpson verdict (models 4–6 in table 1). Our model predicts a spike in anti-Black hate crimes after the October 3 verdict, and consistent with the anti-White hate crimes discussed, we expect a fast rate of decay. Looking first at model 4 in table 1, we observe more evidence of daily and seasonal change for anti-Black than for anti-White hate crimes, which is likely a result of the higher volume of anti-Black hate crimes (cyclical patterns are easier to detect). Net of linear time, anti-Black hate crimes occur more frequently on each day of the week relative to Sundays, and the expected count of anti-Black hate crimes is higher during the summer and fall months (December is the
The parameter of key theoretical interest indicates that during the 4 days immediately after the Simpson verdict, the expected number of anti-Black hate crimes increases by nearly 60 percent ($e^{0.464}$). This association, although statistically significant, is far smaller than what we observed for anti-White hate crimes after the King verdict in 1992, and the effect dissipates more quickly. The coefficients for 6 and 8 days postevent are .286 and .235, respectively, and neither is statistically significant.

Two additional points are noteworthy. First, the postverdict increases in hate crimes for each of the above trials were not confined to California. The proportion of hate crimes in California in the immediate postverdict period (each trial was held in Southern California) changed very little compared with the rest of the year. The backlash seems to have been as likely in New Jersey as in California. This finding is likely attributable to the vast media attention that virtually brought the trial verdicts to millions of American televisions. Second, we are mindful of the possibility that law enforcement may have been more inclined to report hate crimes after the respective verdicts. In supplementary analyses, we reestimated the models using only hate crimes reported by law enforcement agencies that submitted hate crime data to the FBI during the quarters prior to the verdict (first quarter in 1992; first three quarters in 1995; see tables S.1 and S.2 in the online supporting information), which ensures that the police department did not begin complying with the hate crime law after the verdict. When restricting the data in this way, the results remained consistent.

TERRORISM

We next examine hate crimes against Arabs and Muslims after lethal terrorist attacks on U.S. soil in which Islamic fundamentalists were suspected as perpetrators (see the earlier discussion for listing and justification of terrorist acts). In this case, we have multiple events during the observation period, and we assess the duration and decay of any observed effect by including 10 lags of the terrorist attack variable, which indicates the effect of the terrorist attack on hate crimes each of the 10 days after the event. For instance, model 1 in table 2 indicates an initial increase in anti-Arab and anti-Islamic hate crimes on the day of the attack ($b = 2.422$), net of linear time, day of the week, month, and year effects. The coefficient size dissipates in near linear fashion during the next 10 days, but the expected level of hate crime is still higher 10 days after the attack (10-day lag coefficient = $1.542$). An additional analysis shows that lagged coefficients continue to be significant and decrease in magnitude for approximately 1 month, at which point the lagged coefficients are no longer statistically significant.

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8. This holds police department reporting tendencies constant but not police officer or victim reporting tendencies.
Table 2. Negative Binomial Regression Models: Terrorist Attacks and Anti–Arab/Islamic Hate Crimes, 1992–2010

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 (Including Year 2001)</th>
<th>Model 2 (Omitting Year 2001)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lethal Terrorist Attack</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day of attack</td>
<td>2.422*** (.452)</td>
<td>1.471** (.523)</td>
</tr>
<tr>
<td>Lag 1 day</td>
<td>2.506*** (.541)</td>
<td>1.083*** (.353)</td>
</tr>
<tr>
<td>Lag 2 days</td>
<td>2.423*** (.422)</td>
<td>1.532*** (.289)</td>
</tr>
<tr>
<td>Lag 3 days</td>
<td>2.058*** (.518)</td>
<td>.578† (.302)</td>
</tr>
<tr>
<td>Lag 4 days</td>
<td>2.055*** (.442)</td>
<td>.993** (.312)</td>
</tr>
<tr>
<td>Lag 5 days</td>
<td>1.767** (.523)</td>
<td>.114 (.442)</td>
</tr>
<tr>
<td>Lag 6 days</td>
<td>1.838** (.642)</td>
<td>–18.917*** (.580)</td>
</tr>
<tr>
<td>Lag 7 days</td>
<td>1.767** (.527)</td>
<td>.075 (.046)</td>
</tr>
<tr>
<td>Lag 8 days</td>
<td>1.483*** (.414)</td>
<td>.386* (.194)</td>
</tr>
<tr>
<td>Lag 9 days</td>
<td>1.329** (.482)</td>
<td>-.288 (.402)</td>
</tr>
<tr>
<td>Lag 10 days</td>
<td>1.542** (.476)</td>
<td>.128 (.483)</td>
</tr>
</tbody>
</table>

N 6,930 6,565
Wald chi-square 1,334.18*** 2,348.36***
(D.f.) (48) (47)

NOTES: Standard errors are in parentheses. All models control for linear time, the number of anti-Black hate crimes, and dummy variables for day of the week, month of the year, and year. The coefficient for the 6th-day lag in model 2 should be interpreted with caution. No hate crimes were reported the 6th day after a terrorist attack, which resulted in an unusually large coefficient in the model. Omitting this lag has no bearing on the other coefficients.

† p < .10; * p < .05; ** p < .01; *** p < .001.

Given the magnitude of the 9/11 attacks and the sizeable escalation in anti–Arab/Islamic hate crimes immediately thereafter, it is prudent to ask whether the findings are driven entirely by the 9/11 attacks. In model 2, we reestimate the model when omitting the year 2001 from the analysis. The coefficients in model 2 suggest the 9/11 attacks indeed have leverage, but the coefficients remain significant and positive for 6 of the first 11 postevent days (including the day of the attack). As with the trial verdicts, additional

9. The coefficient on the 6-day lagged variable is unreasonably large (–18.917). This is because no hate crimes were reported on the 6th day after terrorist events when the year 2001 is excluded. We do not interpret this single coefficient, and we note
analyses not shown in this article indicate that the location of hate crimes after terrorist attacks does not seem concentrated in the places where the attacks occurred, which is consistent with prior work (Disha, Cavendish, and King, 2011; results not shown here).

Finally, if our theoretical model is correct, then we would expect no association when using other types of hate crimes as the dependent variable or when using nonlethal terrorism as the independent variable. As shown in table S.5 in the online supporting information, this is indeed the case. The lethal terrorism indicators and their respective lags have no association with anti-Black hate crimes. In addition, anti-Arab and anti-Islamic hate crimes are not associated with nonlethal domestic terrorism. Moreover, hate crimes were no more common during the days preceding the terrorist attack. The last model in table S.5 indicates no significant and positive correlation when using “leads” instead of “lags.”

SAME-SEX MARRIAGE LAW

On December 20, 1999, the Vermont Supreme Court made history when it unanimously ruled that same-sex couples were entitled to the same benefits and protections afforded by Vermont law to married heterosexual couples, and in line with our thesis, the number of antigay hate crimes during the next calendar year increased 125 percent, from 4 in 1999 to 9 in 2000. Yet Vermont is a small state with low levels of hate crime, and hence, it is difficult to make inferences based on such small numbers. However, the State Supreme Court for the Commonwealth of Massachusetts issued a similar ruling a few years later on November 8, 2003, which resulted in the legalization of same-sex marriage in the state. Thus, we use the latter case to assess whether antigay hate crimes increased after the Court’s decision. Because the court decision was near the end of the calendar year in 2003, we analyze data from 2003 and 2004, controlling again for several temporal and cyclical indicators (see table 3). The results can be succinctly summarized—we find no conclusive evidence that hate crimes against gays increased after the Massachusetts State Supreme Court decision (table 3).

<table>
<thead>
<tr>
<th>Note</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.</td>
<td>By comparison, other types of hate crimes decreased in Vermont during the same period, and antigay hate crimes in other New England states remained about the same.</td>
</tr>
<tr>
<td>11.</td>
<td>The small number of hate crime offenses in Vermont made regression models highly unstable (i.e., coefficients changed drastically with small changes to model specification).</td>
</tr>
</tbody>
</table>

Also, we do not show the results of the models using the Newey–West standard errors in this study, but they were entirely consistent with the negative binomial models (results shown in the online supporting information, table S.7).
Table 3. Negative Binomial Regression Models: Antigay Hate Crimes in Massachusetts After Goodridge Case

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Four days after decision</td>
<td>1.141</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Six days after decision</td>
<td></td>
<td>.663</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.048)</td>
<td></td>
</tr>
<tr>
<td>Eight days after decision</td>
<td></td>
<td></td>
<td>.309</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.071)</td>
</tr>
<tr>
<td>N</td>
<td>731</td>
<td>731</td>
<td>731</td>
</tr>
<tr>
<td>Wald chi-square</td>
<td>17.81</td>
<td>17.54</td>
<td>17.56</td>
</tr>
<tr>
<td>(D.f.)</td>
<td>(21)</td>
<td>(21)</td>
<td>(21)</td>
</tr>
</tbody>
</table>

NOTES: No coefficients are statistically significant ($p < .05$). Standard errors are in parentheses. All models control for linear time; the number of anti-Black hate crimes in Massachusetts; and dummy variables for day of the week, month of the year, and year (2003 as reference category).

Model 1 indicates a positive coefficient for the 4 days after the decision, and models 2 and 3 show consecutively smaller coefficients, but none are statistically significant. We discuss why these findings likely differ from terrorism and contentious trial verdicts in the next section.

DISCUSSION

The objective of this research was to deepen our understanding of why hate crimes sometimes cluster in time and to improve our understanding of this behavior by focusing on small temporal units and on the role of antecedent events. We proposed an explanation that draws attention to three characteristics: an antecedent event that leaves one group with a grievance against another, a definable out-group to which responsibility for the triggering event was attributed, and publicity to make the event known to a broad public. We found support for this thesis when examining the aftermath of contentious trials and lethal terrorist attacks. With the recent bombing at the Boston Marathon in April 2013 and (at the time of this writing) the pending Trayvon Martin trial, the results seem timely and speak to an issue of importance to both academics and practitioners.12

12. At the time of this writing, we have no data on hate crimes after the Boston Marathon bombing, but initial media reports align with expectations. For instance, the Boston bombing motivated an assault on a Muslim cab driver in Northern Virginia (Stephens and Jouvenal, 2013) and the New York Post reported that a Bangledeshi man was attacked in the Bronx out of revenge for the bombing. The American Arab Anti-Discrimination Committee also expressed deep concern about hate crimes after the bombing.
In addition to explaining in part the temporal variation in hate crimes, the results inform related concepts at the heart of much criminological theory, such as escalation, duration, diffusion, and deescalation of crime. With respect to **escalation**, we suggest hate crimes increase almost immediately after an antecedent event, usually within hours of attribution rather than within weeks. In addition, the rate of **deescalation** seems nearly as rapid as the pace of escalation, and the increases are generally short in **duration**; we tend to observe a spike after an event rather than a plateau. We speculate that anger and prejudice are key emotions driving the retaliatory hate crimes, and prior work has suggested that both anger (Smith, Phillips, and King, 2010) and prejudice (Legewie, 2013) have a half-life, which may account for the deescalation in such a short time. Finally, the effects we observe were **diffuse**. Although not presented in the tables, our inspection of the location of hate crimes after the antecedent events suggests they are not confined to the place of the event.

Not all models performed as anticipated. We expected an increase in antigay hate crimes after appellate court cases that granted rights to same-sex couples, and although the evidence from Vermont provided prima facie support for this notion, we could not corroborate this finding using a more rigorous statistical model with data from Massachusetts. The magnitude and direction of coefficients were consistent with expectations, but the coefficients were not statistically significant. We suggest four plausible reasons why our results differed for the case of antigay hate crime. First, sexual orientation may be more difficult to identify by potential perpetrators, which could limit the opportunity for interpersonal crimes. Offenders may not identify Arabs, Muslims, or racial minorities accurately, but skin hue or religious attire (or religious buildings) may serve as proxies for which sexual orientation has no equivalent. Second, appellate court decisions may not represent shocks to the system in the same way as trial verdicts or terrorist attacks. Court decisions such the *Goodridge* case in Massachusetts instructed the legislature to take action, which then led to debate, and only after several months did the law change. By contrast, the trials culminate in a singular moment with the verdict, and the terrorist attacks serve as immediate shocks to society. Third, and at risk of sounding paradoxical, our analysis may have been conservative by examining a liberal state. Little public opinion data on same-sex marriage is available for the pre-*Goodridge* period, but more recent polling suggests people of the Commonwealth of Massachusetts support same-sex marriage by a 2–1 margin. Were a court to make a similar ruling in a state in which public support is minimal, the reaction may be more intense. This observation, of course, remains speculative and a topic that might be investigated in future research. Finally, we acknowledge that our explanation could place too much emphasis on retribution, when in fact it is the violence associated with terrorism and
homicide cases that begets subsequent violence. Or, perhaps terrorism and contentious trials tap into underlying racism, religious prejudice, and xenophobia in a way that appellate court decisions do not. We cannot adjudicate between these alternative explanations in this work, but we remain open to the possibility that more than retribution is at play.

Before turning to other directions for future work, we briefly address two likely criticisms of this research. One critique is that our focal predictor variables are very rare events, and as such, the model helps explain only a small subset of hate crimes. Two points are relevant to this issue. First, we indeed focus on rare events that have short-term effects on hate crimes; yet in some cases, these events explain a substantial proportion of temporal variation. For example, during the first 10 years in which hate crime data were available from the FBI (1992–2001), approximately 691 hate crimes were reported with a specific anti-Islamic motive. Approximately 66 percent occurred between September 11 and December 31 of 2001—that is, two thirds of the total occurring in 3 percent of the at-risk period. In addition, 15 percent of anti-White hate crimes in 1992 occurred during the 8-day period after the King verdict (8 days is 2.2 percent of the year). It is not always the case that antecedent events explain such a sizeable proportion of temporal variation, but clearly they help us understand a healthy proportion in some cases.

Second is the issue of reporting bias, which was discussed briefly in the data section. We must remain open to the possibility that some of the change we observe is a result of reporting practices; yet we think recent research on attitudes and sentiments supports our argument that a true increase in hate crime behavior is observed after antecedent events. For instance, the results of two natural experiments on views toward immigrants were reported in 2013: one in Europe examining changes in attitudes toward immigrants after the Madrid bombings and the Bali terrorist attack, and a second study that followed Twitter content after the Boston Marathon bombing (Legewie, 2013; Witte, 2013). Each study points to an immediate change in attitudes or sentiments after a terrorist bombing, followed by a fast rate of decay. Given the continuity between research on prejudicial attitudes and the current work on behavior, we think the results reflect actual change and are not simply an artifact of reporting, although the latter interpretation cannot be definitively ruled out.

This work has the potential to motivate additional research. For instance, the theoretical framework advanced in this study would predict

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13. In the Boston case, sentiment about immigration returned to prebombing levels within 10 days, which is very close to the rate of decay found in this study when omitting 9/11.
an association between anti-White and anti-Black hate crimes within cities. Specifically, anti-Black hate crime in a given neighborhood would presumably increase the probability of an anti-White hate crime in the same or an adjacent neighborhood during the subsequent days, assuming that the crimes became known to many people in the area (e.g., through local media). Also, future work might investigate the types of triggers that ignite hate crimes. We found support for two triggers—contentious interracial trials and lethal terrorist attacks—yet what about heinous hate crimes themselves as triggers for additional hate crime, much like Phillips (1983) suggested that violence begets more violence? In addition, criminologists should consider the declaration of war. Public sentiment can be fervent and is likely fueled when leaders demonize an adversary, and some circumstantial evidence aligns with this notion. For instance, hate crimes targeting Arabs and Muslims increased in late March and early April 2003, which corresponds with the start of the Iraq War.

As a final and ancillary point, we mention that the analyses presented in this study, even if modest in their sophistication, were revealing and could not have been possible without data on hate crimes organized by day as opposed to year. Research on the “criminology of place” (e.g., Weisburd, Groff, and Yang, 2012) demonstrated the importance of focusing on the micro geo-unit (e.g., street segments) in the study of crime. We complement work of that nature by drawing attention to the microtemporal units. Prior work has spoken confidently about the hot spots of crime, and hate crime specifically. The current argument demonstrates the utility of investigating the “high times” as well.

REFERENCES


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Ryan D. King is an associate professor of sociology at The Ohio State University. He studies crime, law, and intergroup relations. His recent work focuses on hate crime, skin hue and punishment, and criminal deportations.

Gretchen M. Sutton is a PhD candidate in the Department of Sociology at the University at Albany, State University of New York. Her research interests include gender, race, and crime and intergroup conflict.
SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher’s web site:

Table S.1. Negative Binomial Estimates: Anti-White Hate Crimes after King Verdict ($N = 366$)
Table S.2. Negative Binomial Estimates: Anti-Black Hate Crimes after Simpson Verdict ($N = 365$)
Table S.3. Analysis of Terrorism and Hate Crime when Including Little Rock Incident
Table S.4. Autoregressive Poisson Models
Table S.5. Supplementary Analyses: Hate Crime and Terrorism Models with Alternative Dependent and Independent Variables
Table S.6. GLM Negative Binomial Estimates with Robust Standard Errors: Hate Crimes on Predictor Variables
Table S.7. GLM Negative Binomial Estimates with Newey–West Standard Errors