Echoes of Violent Conflict: The Effect of the Israeli-Palestinian Conflict on Hate Crimes in the United States*

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Abstract

We examine whether social identity ties facilitate the spread of violent conflict. To do so, we assess whether the Israeli-Palestinian conflict causes hate crimes towards Jews and Muslims in the United States using daily data from 2000 to 2016. We measure the timing and intensity, and determine the instigators in the conflict using the number of conflict fatalities and US mass media coverage of the conflict. Analyses using both conflict measures find that conflict events trigger hate crimes in the coming days following a retaliatory pattern: anti-Jewish hate crimes increase after Israeli attacks and anti-Islamic hate crimes increase after Palestinian attacks. There is little evidence that the ethno-religious group not associated with the attacker is subjected to hate crimes during this period. Moreover, the lack of an effect of nonviolent conflict reporting suggests that hate crimes are not triggered by the salience of the Israeli-Palestinian conflict in itself. Our findings show that victimization transcends the locality of the conflict, implying that violent conflict may be more costly than existing research suggests.

Keywords: Conflict, Hate crime, Violence, Israel, Palestine, Media

JEL Codes: D74, K42, J15, L82

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1 Introduction

Since 2010, 31 countries have experienced ethnic civil conflicts, with more than 25 battle-related deaths per year in each of these countries (Vogt et al., 2015). A conservative estimate yields that 330-460 million people have ethnic ties to these conflicts but reside in countries not involved in the conflicts.[1] Research has shown that conflicts are more likely to spill over into other regions or countries when ethnic ties exist (e.g., Black, 2013). One explanation is that violent conflict abroad generates animosity and induces violence at home towards groups with identity ties to the conflict (Bosker and de Ree, 2014). However, this specific transmission channel has not been investigated empirically.

We examine whether social identity ties facilitate the spread of violent conflict. Research on conflict spillovers focuses primarily on cross-border contagion of civil conflict (see, e.g., Black, 2013; Silve and Verdier, 2018), and its economic and financial spillovers (Guidolin and La Ferrara, 2007, 2010; Korovkin and Makarin, 2019). Cross-border ethnic ties have been identified as an important transmitter of conflict and violence (Kuran, 1998) and several studies have concluded that cross-border conflict contagion is more likely when one or more ethnic ties between countries are strong (Buhaug and Gleditsch, 2008; De Groot, 2011; Bosker and de Ree, 2014; Harari and Ferrara, 2018). These studies, however, face important identification challenges. First, what appears to be conflict spillovers might be driven by unobserved regional variables, such as demand or supply shocks, that correlate with ethnic composition.[2] Second, even in the case of actual conflict spillover, it is difficult to disentangle ethnic ties from the vast array of mecha-

[1]These estimates are based on calculations using the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002; Pettersson et al., 2021), the Ethnic Power Relations Dataset (Wucherpfennig et al., 2012) and data from the Joshua Project (joshuaproject.net). First, using the UCDP data and the Ethnic Power Relations Dataset, we identify all civil conflicts that are currently ongoing or ended after 2010 where at least one of the actors involved has made an exclusive claim to fight on behalf of an ethnic group. We then map the ethnic groups involved in the conflicts to data from the Joshua Project, which contains data on the size of ethnic groups in all countries of the world. We then sum the number of individuals who belong to the ethnic group involved in the conflict and reside in a country other than the conflict country.

[2]See McGuirk and Burke (2020) for a recent study on the effect of economic shocks on conflict and for further references.

nisms that have been proposed to spread conflict violence across borders (see, e.g., Blattman and Miguel, 2010; Silve and Verdier, 2018).[3] Third, even if ethnic ties are pivotal for violent spillovers, it is still unclear exactly why. Besides being fuelled by animosity, ethnic violence might spread for instrumental reasons (Weidmann, 2015). For example, the political success of coethnics abroad might shift beliefs about the chances for political success at home, increasing the probability of insurgencies and violent confrontations.

In this study, we empirically isolate the cross-border spread of violence through increasing animosity by looking beyond the geographic and contextual vicinity of the conflicts. By lifting the analysis out of a context where the eruption of civil conflict is at risk, it is unlikely that observed spillovers are caused by unobserved variables or channelled through alternative mechanisms to intergroup animosity. We, thus, also emphasize a largely overlooked consequence of violent conflict: its potential to induce violent criminal behavior in settings far beyond its vicinity. Anecdotal evidence suggests that such violent spillovers can be non-trivial and global. For example, German media reported on clashes between the Turkish and Kurdish diasporas in response to the Turkish military operation into northeast Syria in 2019. In France, the Turkish, Azeri, and Armenian diasporas clashed following the escalating conflict in Nagorno-Karabach in 2020. Following the Russian invasion of Ukraine in February 2022, anti-Russian hate crimes and animosity have been reported in the United States and Europe.[4] In our setting, the Israeli-Palestinian conflict has been reported to trigger hate crimes and animosity primarily against Jews in both the United States and Europe.[5] This type of mechanism is also supported by studies on how anti-Islamic hate crimes are

[3]For instance, cross-border flows of refugees, weapons, and fleeing armed rebel groups are probably more likely to enter neighbouring countries with ethnic ties. If such flows drive conflict spillovers, ethnic ties will spuriously appear to increase the risk of such spillovers.

[4]See e.g. "Brawls between Kurds and Turks Injure Several across Germany", *Deutsch Welle*, October 17, 2019; "Video Shows Turkish and Azeri Nationals 'Looking for Armenians' in France", *The Independent*, October 29, 2020, Accessed 04-08-2021; "Russians Around the World Are Facing Abuse and Harassment Amid the Ukraine Conflict", *The Time Magazine*, March 10, 2022; "Anti-Russian Hate in Europe Is Making Chefs and School Children Out to Be Enemies", *The Washington Post*, March 7, 2022.

[5]See e.g. "2014 Audit of Anti-Semitic Incidents", *Anti-Defamation League*, March 30, 2016; FRA (2018) and Enstad (2017)

triggered by jihadist terrorist attacks targeting the United States. or Western European civilians, such as the 9/11 attacks in the United States or the 7/7 attacks in London (Disha and Cavendish, 2011; King and Sutton, 2013; Hanes and Machin, 2014; Ivandic, Kirchmaier and Machin, 2019). Terrorist attacks have furthermore been shown to induce ethnic discrimination within the criminal justice system (Shayo and Zussman, 2011), even against ethnic groups other than those of the terrorists (McConnell and Rasul, 2021). Yet, these studies on terrorist attacks focus on the effect on hate crimes or discrimination in the country and on the populace under attack, but are mute on how identity ties may facilitate the spread of animosity among individuals who are neither participants in any conflict nor targets of violence.

We contribute to the literature on spillovers of violent conflict by providing causal evidence of how ethnic violence induces violent behavior towards individuals perceived to have identity ties to the conflict actors. We do this by focusing on one of the most long-standing and divisive violent conflicts fought along ethnic and religious lines in the postwar era: the Israeli-Palestinian conflict. Using daily data from 2000 to 2016, we examine whether the Israeli-Palestinian conflict causes hate crimes towards Jews and Muslims in the United States. Since the groups associated with conflict actors in the Israeli-Palestinian conflict map onto distinct hate crime categories, anti-Jewish and anti-Islamic hate crime, this makes the conflict well suited for examining social identities as a channel of conflict spillover.[6] Anti-Jewish and anti-Islamic hate crimes are the two most common categories of religiously motivated hate crimes in the United States, accounting for approximately 12% and 4% of the estimated 250,000 annual hate crimes, respectively (Sandholtz, Langton and Planty, 2013). The geographic and contextual distance between the Middle East and the United States, and our choice to estimate the effect of the Israeli-Palestinian conflict on hate crimes within a time window of a few days, ameliorates several of the endogeneity problems from previous studies. This makes it plausible for us to isolate the effect of animosity transmitted due to the identity

[6]The FBI (2018) defines hate crime as *"a criminal offense committed against a person, property, or society that is motivated, in whole or in part, by the offender's bias against a race, religion, disability, sexual orientation, or ethnicity/national origin."*

of the victim as perceived by the perpetrators.

We use two data sources to measure the intensity of the Israeli-Palestinian conflict. First, we use data on fatal attacks from the Israeli human rights organization *B'Tselem*. Second, we use data on the daily length of US television evening news coverage of the conflict, which we code by attacker, collected from the *Vanderbilt Television News Archive*. Both data sources distinguish attackers from victims, enabling us to examine whether the identity of the attacker matters for which group is victimized in the United States. Compared with the fatalities data, the news data are better at capturing the degree to which US audiences are exposed to events from the conflict and how the events are framed. This is important since previous research shows that the Israel Defense Forces (IDF) appear to time attacks to minimize US news coverage (Durante and Zhuravskaya, 2018), and it is well known that media can play a key role in the spread of violence in general (Dahl and DellaVigna, 2009; Gentzkow and Shapiro, 2004) and ethnic violence in particular (DellaVigna et al., 2014; Yanagizawa-Drott, 2014). The news data also contain information on nonfatal attacks and provide us with a measure of nonviolent conflict news, which we use to test whether the salience of the conflict itself affects hate crimes.

We find the same pattern using both conflict measures: anti-Jewish hate crimes increase after Israeli attacks, and anti-Islamic hate crimes increase after Palestinian attacks. The effects are driven primarily by days with large attacks and days with extensive media reporting. When fatalities from Israeli attacks the same day and the previous day are in the top percentile (40 or more fatal victims), this causes a 35% increase in the expected number of anti-Jewish hate crimes that day. The analogous Palestinian attack (10 or more fatal victims) causes a 44% increase in the expected number of anti-Islamic hate crimes. Similarly, when news reporting on Israeli violence the same day and the previous day in the top percentile (3 minutes or more), this causes a 23% increase in anti-Jewish hate crimes that day. The analogous news reporting on Palestinian violence (2.3 minutes or more) causes a 38% increase in anti-Islamic hate crimes.

The identifying assumption of our empirical strategy is that the timing of conflict news, Israeli attacks and Palestinian attacks are not endogenous to hate crime incidents or hate crime reporting in the United States. This would, for example, be a concern if both conflict fatalities and hate crime levels increase on religious holidays for reasons unrelated to the conflict or if attacks are timed to important events in the United States. that also affect the levels of hate crime. To alleviate such concerns, we control for religious and federal holidays, major political events, and US news pressure. We also find little evidence of violent spillover on ethnic groups that are not associated with the conflict actors (cf. McConnell and Rasul, 2021), which strengthens the claim that the results are not driven by joint periodicity, such as seasonality effects, of conflict intensity and hate crimes in the United States. Furthermore, results are robust to dropping individual states that dominate hate crime reporting, using alternative model specifications and lag structures, as well as to dropping individual conflict periods. In addition, using our news data, we find that news reporting on violence in the 2006 Israel-Lebanon War increased hate crimes against Jews and Muslims in the US, showing that our findings generalize at least to the broader Arab-Israeli conflict.

Taken together, the findings indicate that perpetrators are driven by a retaliatory motive. First, the identity of the attacker matters for which group in the United States. is subjected to hate crimes. Second, there is no effect of nonviolent conflict news on hate crimes. Third, reporting on violence from the conflict does not trigger hate crimes towards Blacks and Hispanics and, thus, there is no general effect of violent news reporting on hate crimes. A plausible explanation for this pattern is that perpetrators of hate crimes identify with attack victims and that conflict violence generates a retaliatory motive against the ethno-religious group associated with the attacker. For example, perpetrators may share an ethnic or religious affiliation with the victimized conflict actor, or may identify with this actor because of political convictions or religious beliefs.[7]

Our findings show how social identities facilitate the spread of violence and contribute to our understanding of how, when and where conflict can have vio-

[7] A possible alternative explanation, which is not mutually exclusive, is that perpetrators do not have such ties, but primarily have strong outgroup biases against Jews and/or Muslims. This could be the case for white supremacists and hate groups. For such a pattern to emerge, violence committed by a specific conflict actor must then more effectively trigger animosity directed towards the associated group in the United States.

lent spillovers. By doing so, we also add to the literature on the determinants and triggers of animosity and hate crimes. Because hate crimes incur greater physical and psychological damages for the individual (Iganski and Lagou, 2015), as well as more severe and persistent costs for the targeted communities, they are considered particularly serious and costly compared with similar non-hate motivated offenses.[8] Thus, we illustrate a previously overlooked negative externality of violent conflicts, implying that the total costs of conflicts are higher than previous estimates suggest (e.g., Abadie and Gardeazabal, 2003; Mueller, 2013, 2017). Our findings can be informative for policy-makers aiming to mitigate or prevent such violence and criminal behavior. This could be relevant both at the domestic level (i.e., for law enforcement agencies) and also for international policy-makers aiming to predict and mitigate the spread of violence.

We structure the article as follows: Section 2 provides a brief background on the conflict and its religious and ethnic dimensions. Section 3 presents the data used in the empirical analysis. Sections 4 and 5 present the empirical strategy and results, respectively, while Section 6 concludes.

2 The Israeli-Palestinian Conflict and Its Religious and Ethnic Dimensions

The Israeli-Palestinian conflict is rooted in the partitioning of Mandatory Palestine into Israel and Palestine by the UN in 1947. The existing borders between the state of Israel and the occupied Palestinian Territories were established in a series of wars in 1948, 1967 and 1973 between Israel and neighboring Arab states, which led to Israel occupying the Gaza Strip and the West Bank. Our analysis covers the period 2000 – 2016 and Section 3.2 describes the conflict dynamics in detail during this period. Although in many ways a territorial conflict between Israelis, Palestinians, and neighbouring states, the conflict also has salient religious and ethnic

[8] For example, Gould and Klor (2016) show that the increase of anti-Islamic hate crimes in the United States in the aftermath of 9/11 had large and lasting effects for the entire US Muslim population, inducing a slowdown of the assimilation of American Muslims, strengthening their ethnic identity, and lowering female labor force participation. See also Dharmapala and Garoupa (2004) and Gan, Williams III and Wiseman (2011).

dimensions, with actors on both sides, for example, using religion as a means of legitimizing their claims on specific territory.

The religious dimension of the conflict is conflated with the ethnic dimension, since both parties to varying degrees depict the conflict as ethnic (see, e.g., Levitt 2008; Klug 2003). This may fuel anti-Jewish and anti-Muslim responses to the conflict. For example, Klug (2003) argues that "hostility towards Israel is liable to spill over into hostility towards Jews as such," implying that Jews in general may become subject to animosity and hate crimes regardless of their religiosity or relationship to Israel. Previous research suggests that the same mechanism may affect Muslims. For example, King and Sutton (2013) show that jihadist terrorist attacks in the United States trigger animosity and hate crimes directed at American Muslims. We hypothesize that a similar mechanism is at play in the Israeli-Palestinian conflict, although Israeli and Palestinian attacks occur in the context of a two-sided conflict, are not directed towards Americans or Westerners, and are not proximate to either victims or perpetrators of hate crimes.

To the extent that potential hate crime perpetrators in the United States associate Jews, Muslims, and Arabs with actors in the conflict, these groups risk becoming subject to hate crime when the conflict flares up. In 2015, the Jewish population in the United States was estimated to be 6.7–6.8 million (Dashefsky and Sheskin, 2015). The total number of US citizens who consider themselves to have direct ancestry to Palestine, or any of the surrounding Arab countries that have been directly or indirectly involved on the Palestinian side, is estimated to be 1.9 million (US Census Bureau, 2016).[9] A 2016 Gallup survey found that 2.1% of the US population identify as Jewish and 0.8% identify as Muslim.[10]

[9]The US Census Bureau defines *ancestry* as the "ethnic origin, descent, 'roots', heritage, or place of birth of the person or of the persons ancestors" (De la Cruz and Brittingham, N.d.). We include descendants of Algerian, Bahraini, Egyptian, Emirati, Iraqi, Jordanian, Kuwaiti, Lebanese, Libyan, Moroccan, Omani, Palestinian, Qatari, Saudi Arabian, Syrian, Tunisian, and Yemeni origin.

[10]"Five Key Findings on Religion", Gallup, December 23, 2016.

3 Data

This section describes the data on hate crime incidents, conflict fatalities, and conflict news, and presents an analysis validating that our measurement of conflict news captures significant events in the conflict.

3.1 Hate Crime Data

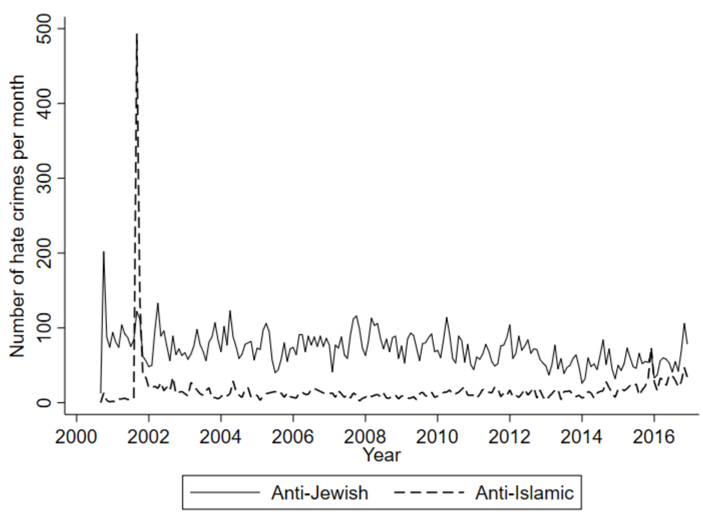
We obtained data on hate crimes in the United States from the Uniform Crime Reports (UCR) database, provided by Federal Bureau of Investigation (FBI) and accessed from Kaplan (2018). Under the Hate Crime Statistics Act of 1990, all law enforcement agencies in the United States are asked to submit counts of hate crime incidents in their jurisdiction.[11] Participation is voluntary for agencies and has gradually increased during our period, increasing from 11,690 agencies in 2000 to 15,254 agencies in 2016. This accounts for 90% of all agencies, covering 290 million people, or 90% percent of the US population (FBI, 2018). Existing research shows that participation of agencies is related to demographic and political characteristics of jurisdictions (see, e.g., King 2007; McVeigh, Welch and Bjarnason 2003). Underreporting of hate crimes, on the part of both police agencies and individuals, is a well-documented and persistent problem (see, e.g., Sandholtz, Langton and Planty 2013; King, Messner and Baller 2009). To ameliorate the selection problem, we estimate the effect of the conflict on hate crimes by comparing the number of reported hate crimes within the span of a few days after an attack or event. Consequently, it is unlikely that any reporting bias across jurisdictions or over longer time periods pose a threat to establishing causality. However, since we are using data on reported hate crimes, we cannot rule out that the treatment effects could reflect a short-term change in reporting behavior among police agencies or victims and not actual changes in the prevalence of hate crime incidents.

Anti-Jewish hate crimes are the second most common hate crime category in the data, after anti-Black hate crimes, and constitute around 13% of all hate crimes. Thus, these are the most common religiously motivated hate crimes, followed by

[11] If possible, the agencies should provide data on the nature of the offense, location, and characteristics of the offender and victim.

anti-Islamic hate crimes, at 2%. Figure 1 shows the monthly number of reported anti-Jewish and anti-Islamic hate crimes between 2000 and 2016 in the United States. The two types of hate crimes converge during the period: anti-Jewish hate crimes steadily decrease, while anti-Islamic hate crimes increase somewhat.[12] Two distinct spikes in hate crimes are seen. Anti-Jewish hate crimes spiked in October 2000, coinciding with the start of the Second Intifada[13]. Anti-Islamic hate crimes peaked in weeks and months following the 9/11 terrorist attacks, as documented by King and Sutton (2013) and Byers and Jones (2007). Since this period of extreme anti-Muslim hate crime levels coincided with the Second Intifada, we omit the six months following the 9/11 attacks from our main analysis.

Figure 1: Number of anti-Jewish and anti-Islamic hate crimes in the United States aggregated per month



Note: Data from FBI (2018). The figure shows the number of anti-Jewish and anti-Islamic hate crimes per month in the United States between September 29, 2000, and December 31, 2016. Note that this figure includes the 9/11 period, which we exclude in the other figures and tables that contain hate crime data.

[12]Long term trends in reported incidents might reflect trends in reporting or agency participation and should be interpreted with caution.

[13]This period of intense fighting commenced in September/October 2000 with a number of controversial events, including the visit of Ariel Sharon to the Temple Mount. The connection between the start of the Second Intifada and hate crimes in the United States was also identified by various US news outlets in October 2000. See, for instance, "New Hostility in Mideast Echoes in a Brooklyn Neighborhood", New York Times, October 5, 2000.

Our data contain 13,652 accounts of anti-Jewish hate crimes and 2,606 accounts of anti-Islamic hate crimes. Anti-Islamic hate crime offenses more often include aggravated and simple assault, while most anti-Jewish hate crimes in our sample are vandalism offenses. Geographically, most anti-Jewish hate crimes occurred in New York, New Jersey and California, while most anti-Islamic hate crime occurred in California, Michigan, and New York. The most common location for both anti-Jewish and anti-Islamic hate crimes is at the residence of the victim. Both types of hate crimes are distributed uniformly across the month of the year and day of the week. Appendix Tables A1 and A3 show summary statistics for the type, location and seasonal variation of anti-Jewish and anti-Islamic hate crimes in our sample.

3.2 Data on the Israeli-Palestinian Conflict

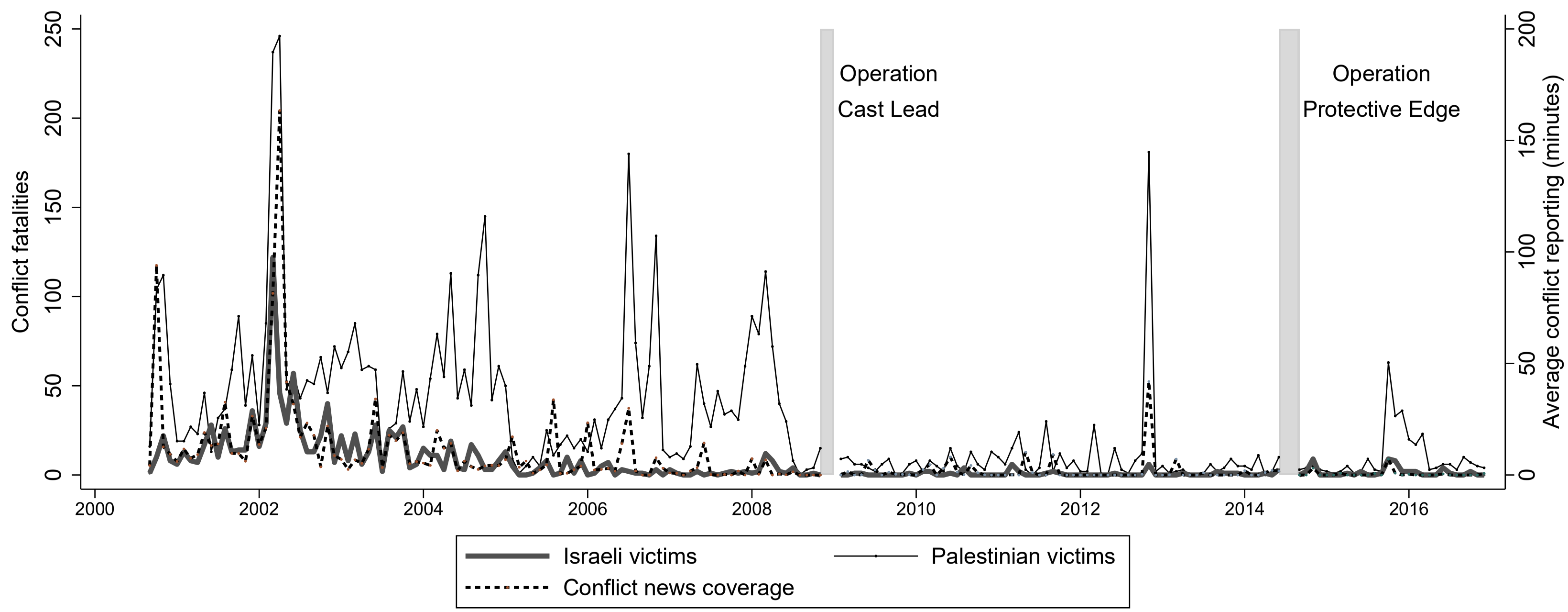
Data on attacks by Israelis and Palestinians comes from the Israeli Information Center for Human Rights *B'Tselem*.[14] The data include every fatal attack by the IDF or Palestinian militants from Sptember 29, 2000, the start of the Second Intifada, to the end of 2016, are included.

As can be seen in Figure 2, our sample period is characterized by periodically intense fighting between the Israeli Defense Forces and Palestinian militants. In September 2000, Palestinians initiated an uprising against the Israeli occupation, the Second Intifada, which lasted until 2005, claiming approximately 3,000 Palestinian and 1,000 Israeli civilian and military lives. The Second Intifada was initiated after Ariel Sharon, then candidate for Israeli prime minister, made a visit to the Temple Mount. This led to protests among Palestinians, at times violent, which were struck down by the Israeli army. The confrontations intensified with a major military operation, Operation Defensive Shield, launched by Israel into the West Bank in 2002, and several suicide bombings directed against Israelis by Palestinian militants. The five years of the Second Intifada account for 78% of Israeli casualties and 35% of Palestinian casualties in our sample.

After the Second Intifada, the conflict was characterized by long periods of

[14] The B'Tselem data are commonly used in scholarship on the Israeli-Palestinian conflict (,e.g., Jaeger and Paserman, 2008; Haushofer, Biletzki and Kanwisher, 2010; Durante and Zhuravskaya, 2018)

Figure 2: Number of conflict fatalities and minutes of conflict news per month



Note: Data from FBI (2018). The figure shows the number of anti-Jewish hate crimes, the number of anti-Islamic hate crimes, and the total minutes of conflict news coverage on ABC, CBS, and NBC per month in the United States between September 29, 2000, and December 31, 2016, with the exception of two particularly intense conflict periods: Operation Cast Lead and Operation Protective Edge. We exclude these conflict periods to make the graph more legible. We present descriptive statistics on fatalities for the excluded conflict periods in Table 1.

low-intensity fighting alongside highly intensive conflict periods due to three major Israeli military operations. The three operations shared the stated purpose of halting rocket attacks from the Gaza Strip into Israel. In December 2008, Israel initiated Operation Cast Lead, also known as the Gaza War, inside the Gaza Strip. The subsequent three weeks of fighting resulted in over 1,000 Palestinian fatalities and 13 Israeli fatalities. In 2012, Israel launched Operation Pillar of Defense, as a response to intensified exchanges between Palestinians and Israel. The eight-day operation resulted in approximately 150 Palestinian casualties and 6 Israeli casualties. In 2014, Israeli launched a seven-week military operation, Operation Protective Edge, in the Gaza Strip. Rocket attacks had intensified following another Israeli military operation in Gaza, a response to the kidnapping and murder of three Israeli teenagers by Hamas members. Approximately 1,200 Palestinians and 70 Israelis were killed during the operation. The three military operations cover approximately 1.3% of the sample days, but account for 40% of Palestinian casualties and 7% of Israeli casualties.

Table 1 presents summary statistics of attacks by and fatalities on each side for eight conflict periods. The table shows the total number of victims of Israeli and Palestinian attacks, the average number of victims per day, and the share of days when an attack took place, for each conflict period and for the entire sample. The Israeli military operations Cast Lead, Pillar of Defense, and Protective Edge were particularly intense, resulting in 61, 22 and 46 fatalities per day on average, respectively. In contrast, the periods between Cast Lead and Pillar of Defense and after Protective Edge were characterized by less intense violence, with 0.26 and 0.38 fatalities per day on average, respectively, driven mostly by Palestinian victims. The incidence of fatal attacks was generally high. A fatal attack occurred on 35% of the days in our sample, averaging 1.7 victims. This was mainly driven by the high frequency of fatal Israeli attacks. While only 7% of the days in our sample had at least one Israeli victim, 35% of the days had at least one Palestinian victim. There is considerable overlap between days with Israeli victims and days with Palestinian victims, especially with regards to Palestinian attacks. In fact, 70% of days with a fatal Palestinian attack also had a fatal Israeli attack. Conversely, 15% of days with a fatal Israeli attacks also have fatal Palestinian attacks. As shown by Haushofer, Biletzki and Kanwisher (2010), who replicate the findings of Jaeger and Paserman (2008), the conflict followed a retaliatory pattern in which each side to some degree immediately responded to violence by the other side.

Columns (5) – (8) in Appendix Table A1 present summary statistics of the total number of fatalities on each side and the distribution across days of the week and calendar months. The Palestinian attacks resulted in a total of 1,111 Israeli victims, and the Israeli attacks in 9,036 Palestinian victims. Neither Israeli nor Palestinian attacks show a strong clustering on weekdays compared wtih weekends. Victims from Palestinian attacks are evenly distributed over the months, while those from Israeli attacks are clustered in January and July, which is primarily driven by the Israeli operations *Cast Lead* and *Pillar of Defense*, which took place during those months. Appendix Table A2 provides similar descriptive statistics for the main variables used in the analysis.

Table 1: Conflict fatalities and US media reporting, by conflict period

	2nd Intifada (29sep2000–15jan2005)	2nd Intifada - Op. CL (15jan2005–26dec2008)	Operation Cast Lead (27dec2008–18jan2009)	Op. CL - Op. PoD (19jan2009–13nov2012)	Operation Pillar of Defense (14nov2012–21nov2012)	Op. PoD- Op. PE (22nov2012–7jul2014)	Operation Protective Edge (8jul2014–26aug2014)	Post Op. PE (27aug2014–31dec2016)	Total
Days in period	1570	1441	23	1395	8	593	50	858	5938
Fatalities									
Israelis									
Fatalities	957	106	9	26	6	10	69	45	1228
Fatalities/day	.61	.07	.39	.02	.75	.02	1.38	.05	.21
Daily incid. of fat.	.19	.04	.22	.01	.38	.01	.32	.03	.07
Palestinians									
Fatalities	3237	1669	1398	342	169	78	2222	283	9398
Fatalities/day	2.06	1.16	60.78	.25	21.13	.13	44.44	.33	1.58
Daily incid. of fat.	.61	.36	1	.12	1	.09	.9	.2	.35
Total									
Fatalities	4194	1775	1407	368	175	88	2291	328	10626
Fatalities/day	2.67	1.23	61.17	.26	21.88	.15	45.82	.38	1.79
Daily incid. of fat.	.66	.38	1	.13	1	.1	.9	.21	.35
US Conflict Reporting									
Minutes/day covering...									
Israeli attacks	.32	.04	4.84	.04	.17	.02	1.91	0	.14
Both sides attacking	.61	.09	3.86	.01	10.73	.04	3.57	.01	.25
Palestinian attacks	.34	.04	0	0	1.25	.02	.34	.01	.11
Nonviolent news	.33	.2	.08	.08	0	.09	.26	0	.17
Total	1.6	.38	8.78	.13	12.15	.16	6.08	.03	.67
Share of days with reporting	.4	.12	1	.04	.88	.04	.78	.02	.16

Note: Data from the *B'Tselem*. The exact sample period is September 29, 2000, to December 31, 2016, including the 9/11 period. The upper panel of the table shows descriptive statistics for both Israeli and Palestinian fatal attacks split into eight specific conflict periods and, in the last column, for the total sample period. The conflict periods are described in the top row of the table. For each conflict period, the table shows the number of days in the period, the total number of Israeli and Palestinian fatalities, Israeli and Palestinian fatalities per day on average, and the average daily incidence of Israeli and Palestinian fatal attacks. The last three rows show the same statistics for Israeli and Palestinian fatalities combined. The bottom panel shows the average length of US conflict news reporting on the conflict from NBC, ABC, CBS, and all three networks combined per day. The last row shows the share of days with conflict reporting.

3.3 Conflict News Data and its Association with Conflict Fatalities

To measure US mass media coverage of the Israeli-Palestinian conflict, we collect information from the evening news on three major TV networks from the Vanderbilt Television News Archive (VTNA). We focus on the three major networks that have a well-defined 30-minute time slot for evening news every day: ABC, CBS, and NBC. These major evening broadcasts have roughly equal market shares, and together they reached on average around 20 million US households per evening in 2016.[15]

VTNA contains more than 15,000 evening news broadcasts and more than 200,000 individual news stories for the years 2000 – 2016. For each individual news story, VTNA provides a headline, a summary, the length in seconds, and the order of appearance of the story in the full evening news broadcast. To identify news stories about the conflict, we start by following Durante and Zhuravskaya (2018) and search for all stories with headlines containing the words Israel, Jerusalem, Tel Aviv, Palestine, Gaza, West Bank, or Hamas, or any words with related roots. This yields a total of 2,367 stories. To exclude stories unrelated to the conflict, such as news about Israeli or Palestinian politics, culture or tourism, we apply a word filter to the story headlines and summaries. First, we include stories that have a headline referring both to the Israeli and Palestinian references mentioned above. Second, we include stories with a headline containing an Israeli reference and no Palestinian reference, but that have a summary containing any of the Palestinian references. Analogously, we also include stories that have a Palestinian reference in the headline and no Israeli reference, but which have a summary containing an Israeli reference. We obtain a total of 1,747 stories about the conflict using this method. We proceed to manually code whether the news segments focus on Israeli violence, Palestinian violence or violence on both sides.[16] This results in 314 news segments focusing exclusively on Israeli violence, 387 news segments focus-

[15]See "Network News Fact Sheet", *Pew Research*, July 13, 2021.

[16]If the news segment mentions explicit violence from one side directed against the other, we classify this as reporting on violence. If the segment mentions violence, but it is unclear who the attacker is, we code it as violence from both sides.

ing exclusively on Palestinian violence, 530 segments mentioning violence on both sides, and 516 news segments not mentioning violence between the groups at all. Appendix Table A4 gives five examples of news stories and our application of the filter.

Our principal measure of conflict news on a particular day is the average length of conflict-related news stories mentioning Israeli violence, Palestinian violence, or violence on both sides on NBC, ABC, or CBS. To capture the overall newsworthiness of conflict-related stories, we divide the total length of conflict stories by the number of evening news broadcasts from the three networks that were recorded on a particular day. Consequently, our measure is discounted if one or two networks do not consider a particular conflict related event newsworthy enough to include on the evening news. Our measure, thus, captures how newsworthy these national networks consider each-conflict related story on a particular day and provides a proxy for daily mass media coverage of the Israeli-Palestinian conflict in the United States.

The bottom part of Table 1 presents summary statistics of the different types of news coverage of the conflict during the different conflict periods. During the whole period, the conflict was covered on 16% of all days for an average of 40 seconds per news broadcast. Of course, reporting is much more intense when the conflict flares up. For example, the evening news featured the conflict everyday during Operation Cast Lead and 9 out of 10 days during Operation Pillar of Defense. However, during the three year period between these operations, the conflict was covered only once every 20 days on average.

We investigate the validity of the conflict news measure by examining its association with conflict fatalities. Figure 2 plots the number of Israeli and Palestinian casualties together with total conflict news coverage, not split by attacker, for the entire sample period, excluding the extraordinarily intensive fighting in the Gaza Wars of 2008-2009 and July 2014. The figure illustrates that our measure of conflict news correlates strongly with conflict fatalities, but also that there is considerable variation not explained by conflict fatalities. The figure also shows that, with the important exception of the excluded short periods of intense fighting, day-to-day casualties were fewer in the later period. While the period of the Second Intifada, roughly 2000 to 2005, exhibited substantial turbulence and victims on both sides, the period after the first Gaza War was characterized by longer periods of relative calm.

We formally test this relationship by regressing the length of violent conflict news on each side on three lags of fatalities from Israeli and Palestinian attacks using least squares with fixed effects for year, month, and day of the week. The results are shown in Table 2. Our primary interest is the joint significance of the lags, shown in the bottom panel of the table. The table shows that when there were Palestinian victims from Israeli attacks reporting on Israeli violence and reporting on violence from both sides significantly increased, but it has no effect on nonviolent conflict news. An Israeli attack with 9 Palestinian fatalities (corresponding to one standard deviation) increases coverage of exclusive Israeli violence by 24 seconds. The effect on exclusive reporting on Palestinian violence is predominantly negative but only significant at the 10% level. Turning to the effect of Israeli victims from Palestinian attacks, we see a strong, significant and positive effect on exclusive reporting of Palestinian violence and violence on both sides, but strong, significant negative effects on exclusive reporting of Israeli violence and nonviolent conflict news. A Palestinian attack with 1.2 Israeli fatalities (corresponding to one standard deviation) increases coverage of exclusive Palestinian violence by 8.5 seconds. The significance of the individual coefficients from both Israeli and Palestinian attacks indicates that attacks the same day and the previous day are particularly important for conflict news coverage.

The percentage of explained variation ranges from 7% for nonviolent reporting to 21%-37% for violent reporting. We examine how much of the conflict news reporting is driven by fatal attacks by comparing the share of explained variation to a set of benchmark models, which include only fixed effects and control variables. We find that the share of explained variation for reporting on Israeli violence increases by 16 percentage points, for Palestinian violence by 27 points and for violence on both sides by 22 points. For nonviolent reporting, the difference is a mere 0.03 points. Thus, for reporting on violence, the share of explained variation more than quadruples when we add conflict fatalities to the model, further strengthening the validity of our measurements.

Table 2: Effect of fatal attacks on conflict news content

	(1) Israeli Violence	(2) Palestinian Violence	(3) Violence on Both Sides	(4) No Violence
Victims Israeli attacks day...				
(t)	0.009**	−0.001	0.007	0.000
	(0.003)	(0.001)	(0.004)	(0.000)
($t-1$)	0.010*	−0.001	0.004	0.001
	(0.004)	(0.001)	(0.003)	(0.001)
($t-2$)	−0.000	0.001	0.009	0.001
	(0.003)	(0.002)	(0.006)	(0.001)
Victims Palestinian attacks day...				
(t)	−0.024**	0.116***	0.075***	−0.012***
	(0.007)	(0.012)	(0.020)	(0.003)
($t-1$)	−0.001	0.049***	0.062***	0.002
	(0.008)	(0.013)	(0.017)	(0.008)
($t-2$)	0.008	0.012*	0.068*	−0.002
	(0.012)	(0.006)	(0.033)	(0.005)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure	Yes	Yes	Yes	Yes
Observations	5698	5698	5698	5698
Mean dependent var.	0.054	0.038	0.089	0.064
SD of dependent var.	0.354	0.281	0.558	0.337
Model	OLS	OLS	OLS	OLS
F-test Israeli attacks	0.000	0.068	0.006	0.369
F-test Palestinian attacks	0.015	0.000	0.000	0.002
R-squared	0.216	0.366	0.268	0.071
R-squared excluding attacks	0.048	0.089	0.048	0.068

Note: The outcome variables are the minutes of conflict news categorized by content. Independent variables are the number of fatal victims from Israeli attacks and from Palestinian attacks. The corresponding F-test refers to the p-value of the restricted model where the effects of attacks on each side are null. R-squared excluding attacks refers to the R-squared from models where the outcome variables are regressed on the controls and fixed effects. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays and events described in Section 4.1. All models are estimated using OLS, with Newey-West standard errors allowing for autocorrelation of up to seven lags in parentheses.
* $p < 0.05$, ** $p < 0.01$, $^{***}p < 0.001$

Although our models account for a substantial part of the variation in conflict news, most of the variation remains unexplained. Importantly, this reflects that our conflict news measures capture more information than a simple fatality count. First, our measure of conflict news likely reflects the newsworthiness of a particular attack, which will not be perfectly captured by the total number of fatalities. For example, certain attacks, such as suicide bombings or attacks with many civilian victims, may be particularly controversial and considered more newsworthy. Second, US mass media covers events in the conflict not reflected in the number of fatalities, such as rioting and nonfatal rocket attacks. In sum, we conclude that our measures of conflict news are meaningfully associated with fatal attacks in the conflict.

4 Empirical Strategy

We examine how conflict intensity affects the incidence of hate crimes using two types of data described in detail in the preceding sections. The first is based on conflict fatalities, a direct measure of conflict intensity. Our data allows us to distinguish the identity of the attacker and the victims, and we use this information to examine the mechanism through which conflict fatalities trigger hate crimes. We hypothesize that fatal aggression generates more hate crimes towards the ethno-religious group associated with the attacker. While the salience of the conflict should increase in the aftermath of an attack, animosity should increase primarily toward the attacker. To test this, we estimate

$$Hate_{tk} = \gamma + \alpha_I^k \sum_{\tau=(t-1)}^{t} Isr\,Att_\tau + \alpha_P^k \sum_{\tau=(t-1)}^{t} Pal\,Att_\tau + \boldsymbol{\omega}_t + \boldsymbol{\delta}_{y_t} + \boldsymbol{\eta}_{m_t} + \boldsymbol{\rho}_{d_t} + \epsilon_{tk} \quad (1)$$

where $Hate_{tk}$ is the number of hate crimes toward group k (either Jews or Muslims) on day t, α_I^k is the effect of the number of Palestinian fatal victims from an Israeli attack day t, and $t-1$. α_P^k estimates the effect of Palestinian attacks. In our main specification, we focus on the effects of attacks the same day and the previous day, since the media analysis presented in Table 5, suggests that fatal attacks primarily increase conflict news primarily on these days. Including one lag of fatalities allows enough time for potential offenders to be reached by, and react to, information about the event.[17] We include in all main specifications a vector of control variables, $\boldsymbol{\omega}_t$, which we explain in detail in Section 4.1, as well as fixed effects for

[17] The 6-to-10 hour time difference between the United States and Israel implies that if a significant event occurs in Israel shortly after midnight, for example at 1 a.m., this would be 3(6) p.m. on the US West (East) Coast the previous day. Since we do not have information on the time of the day when attacks or hate crimes occur, but only the dates on which they occur, this makes it possible for both media outlets and individuals to react to events in the Middle East the day before they are reported to happen. For to the same reason, the time difference enables a response in the United States on the same calendar date as the conflict event.

year, δ_{y_t}, calendar month, η_{m_t}, and day of the week, ρ_{d_t}. This is to ensure that the relationship between hate crimes and conflict intensity is not driven by time trends or seasonality. This would, for example, be the case if conflict intensity and propensity to report hate crimes in the United States increased during our period for unrelated reasons, or if both attacks and hate crimes are more common during certain calendar months or weekdays.[18] ϵ_t is the idiosyncratic error term. As our dependent variable is count data and exhibits overdispersion, we use a maximum likelihood negative binomial model in all our main specifications. To account for serial correlation of hate crime levels and conflict fatalities, we estimate standard errors using the Newey-West estimator, allowing for autocorrelation of up to seven lags.

While the fatalities data is a clear measure of events in the conflict, it lacks nuance that is likely important in our setting. Using our measure of US mass media coverage of the conflict, coded by who is reported to be the attacker, we can complement equation (1) in several ways. First, the context of the attack, not captured by the number of fatalities, may affect both reporting and any behavioral response. Our media measures capture the general newsworthiness of conflict events to a US audience better than a fatality count. Second, conflict events are unlikely to trigger hate crimes if potential offenders never learn about them. The media measures are better at capturing the degree to which US audiences are exposed to information about the conflict and how this information is framed. For instance, although there may be fatalities on both sides on a specific day, the individual news segment may focus on aggression from one side. Third, the media measures capture attacks and violence that are not fatal, such as rocket attacks, failed suicide bombings, and kidnappings. Hence, we complement equation (1) by estimating:

$$\begin{aligned} Hate_{tk} = \phi + \beta_I^k \sum_{\tau=(t-1)}^{t} Isr\ Att\ Rep_\tau + \beta_P^k \sum_{\tau=(t-1)}^{t} Pal\ Att\ Rep_\tau + \beta_{IP}^k \sum_{\tau=(t-1)}^{t} Both\ Att\ Rep_\tau \\ + \boldsymbol{\omega}_t + \boldsymbol{\delta}_{y_t} + \boldsymbol{\eta}_{m_t} + \boldsymbol{\rho}_{d_t} + \epsilon_{tk} \end{aligned} \tag{2}$$

[18]We also test for the presence of unit root in the main time series variables for fatalities, media reporting, and hate crimes, using an augmented Dickey-Fuller test. The tests show that we can reject the null of a unit root for all time series ($p < 0.01$ for all variables), implying that they are stationary.

where β_I^k denotes the effect of the average length of conflict news focusing on day t and $t-1$ exclusively on Israeli violence, β_P^k the effect of conflict news focusing exclusively on Palestinian violence, and β_{IP}^k the effect of news reporting on violence from both sides. The dependent variable, the fixed effects, and the control variables are the same as in equation (1) and we also use a negative binomial model with Newey-West standard errors. In Section 5.4, we also show that our results are robust to a range of alternative specifications and estimation techniques, including alternative lag structures, OLS estimates of linear and log-linear models, probit model estimates, added leads of the independent variables, and added lagged dependent variables. Note that we cannot disentangle the effect of conflict news from the conflict events themselves, nor can we exclude that conflict information may have reached potential perpetrators through other information channels, such as alternative media sources focusing on the Middle East (e.g., Al Jazeera), social media, or personal contacts in the region.

Does the identity of the attacker matter for what group is subjected to hate crimes? This would imply that the effect of fatal attacks and media reporting on violence differs depending on the attacker and what group in the United States is targeted. We examine this in two ways. First, we compare the effect of the different attackers within the same hate crime category. For example, do Israeli and Palestinian attacks differ in their effects on anti-Jewish hate crimes? Formally, we test whether $\alpha_I^k = \alpha_P^k$ and $\beta_I^k = \beta_P^k$. Second, we compare the effect of the same attacker across hate crime categories. For example, do Israeli attacks have the same effect on both anti-Jewish and anti-Islamic hate crimes? To test this, we estimate equations (1) and (2), respectively, as a system of seemingly unrelated regressions between the two hate crime categories. We then test whether, for attacker i, $\alpha_i^{jew} = \alpha_i^{isl}$ and $\beta_i^{jew} = \beta_i^{isl}$.

4.1 Controls

The identifying assumption underlying a causal interpretation of the estimates is that the timing of fatal attacks and conflict news is exogenous with regards to the timing of anti-Jewish and anti-Islamic hate crimes in the United States. We strengthen the identifying assumption by including controls for religious holidays, federal holidays, US news pressure, and US political events that drive hate crimes.

Religious and national holidays may affect both the likelihood of Israeli and Palestinian attacks and the salience of group membership among Jews and Muslims in the United States, which in turn may affect the number of hate crimes. This can lead to a spurious correlation between conflict events and anti-Jewish and anti-Islamic hate crimes. We therefore include a set of controls for Jewish, Israeli, Islamic, and Palestinian holidays and events, listed in Appendix Table A5. Conflict events may also coincide with days or periods during which the incidence of hate crimes in the United States is systematically different. For example, attacks may be timed to Christian or federal holidays if these holidays affect news consumption levels. If such holidays are associated with systematically different numbers of hate crimes, this will bias the estimates. We therefore control for a set of Christian and federal holidays, as well as the annual 9/11 anniversary. These holidays and events are also listed in Appendix Table A5.

Durante and Zhuravskaya (2018) show that Israeli attacks are more likely to occur the day before US news is dominated by important predictable events. Their analysis suggests that the strategic timing applies to attacks that bear risk for civilian casualties in order to minimize next-day coverage. Failure to account for the strategic timing could generate both an upward and a downward bias.[19] To address this concern, we control for major political and sports events that are *ex ante* predictable, generate higher levels of news pressure, and are themselves unlikely to trigger news reporting on the conflict. The events included, together with a description of how we select them, are listed in Appendix Table A5. To further

[19]We consider three examples of strategic timing. First, consider the case where attacks are timed to political events in the United States, which have no effect on hate crimes. This decreases the probability that potential hate crime offenders are exposed to information about attacks, and would reduce but not bias the estimated effect of conflict fatalities on hate crimes, while our estimated effect of conflict news would be unaffected. Second, consider the same strategic timing, but where the predictable political events are associated with increased numbers of hate crimes. In this case, the estimated effect of fatalities on hate crimes could be biased either upwards or downwards, while the estimated effect of conflict news on hate crimes will be biased upwards. Third, consider again the same strategic timing, but where the predictable events are associated with lower numbers of hate crimes. In this case, the estimated effect of both fatalities and conflict news on hate crimes will be biased downwards.

address this concern, we directly control for US news pressure the same day as the attack and the next day. We construct the news pressure variable following Eisensee and Strömberg (2007), using the length of news stories unrelated to the Israeli-Palestinian conflict in the evening news broadcasts on ABC, CBS, and NBC.

5 Does the Israeli-Palestinian Conflict Trigger Hate Crime?

5.1 The Effect of Conflict Fatalities on Hate Crime

We present the main results of estimating equation (1) in Table 3. Columns (1) and (2) regress hate crimes on the number of victims from Israeli and Palestinian attacks. The table shows that Israeli attacks trigger anti-Jewish hate crimes and Palestinian attacks trigger anti-Muslim hate crimes. The average fatal attack, corresponding to 6.61 victims from Israeli attacks and 3.22 victims from Palestinian attacks, increases the number of expected hate crimes towards Jews by 1.4% and towards Muslims by 8.7%.[20] Appendix Table A7 presents alternative models with up to five individual lags of the independent variables. The results are largely consistent, and suggest that the most pronounced effect is from attacks the day before.

Our fatalities data are strongly right-skewed, and in columns (3) and (4) we show that large attacks are especially important in driving our results. We regress hate crimes on two sets of dummies indicating whether an attack is below or in the top percentile of the distribution of attacks for each side, including days with no attacks. This yields an indicator for 57 dates with more than 40 Palestinian fatalities and 46 dates with more than 10 Israeli fatalities.[21] The reference category is days with no attacks. The effects for large attacks mirror our findings from the linear specification. A large Israeli attack increases anti-Jewish hate crimes by 35% and

[20]The negative binomial model uses a log-link function and the coefficients can be interpreted as $exp(\beta)\%$ change in the outcome variable.

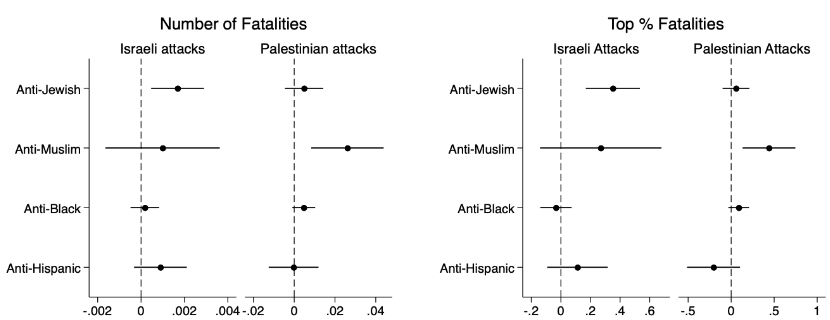
[21]We construct the dummies based on the distribution of attacks from each side, since, as we show in Table 2, the effect of conflict fatalities on conflict news differs between the attackers.

Table 3: The effect of conflict fatalities on hate crime

	(1) Anti-Jewish	(2) Anti-Islamic	(3) Anti-Jewish	(4) Anti-Islamic
Victims Israeli attacks (t and $t-1$)	0.002^{**}	0.001		
	(0.001)	(0.001)		
Victims Palestinian attacks (t and $t-1$)	0.005	0.026^{**}		
	(0.005)	(0.009)		
Top 1% Israeli attacks (t and $t-1$)			0.351^{***}	0.269
(> 40 victims, 57 dates)			(0.093)	(0.209)
Top 1% Palestinian attacks (t and $t-1$)			0.056	0.440^{**}
(> 10 victims, 46 dates)			(0.080)	(0.157)
Smaller Israeli attacks (t and $t-1$)			0.032	0.047
(1 − 40 victims, 2635 dates)			(0.023)	(0.051)
Smaller Palestinian attacks (t and $t-1$)			0.032	0.066
(1 − 10 victims, 639 dates)			(0.034)	(0.075)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes
Observations	5763	5763	5765	5765
Mean dependent var.	2.366	0.452	2.368	0.452
SD of dependent var.	1.843	0.732	1.845	0.732
Model	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.031	0.051	0.032	0.051
p-value $\alpha_I^{Jew} = \alpha_I^{Isl}$	0.328		0.578	
p-value $\alpha_P^{Jew} = \alpha_P^{Isl}$	0.023		0.013	
p-value $\alpha_I^k = \alpha_P^k$	0.527	0.008	0.020	0.549

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) and (3)) and Muslims (columns 2 and 4). The independent variables are the total number of victims the past two days from Israeli attacks and Palestinian attacks (columns (1) − (2)) and two mutually exclusive dummy variables indicating smaller and top percentile Israeli and Palestinian attacks (columns 3 − 4). All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses. The last three rows present the p-values of a test for equality between the effects of Israeli or Palestinian (large) attacks on anti-Jewish and anti-Islamic hate crimes estimated using seemingly unrelated regressions, or a test for equal effects for Israeli and Palestinian attacks within the same model.
$^{*}\ p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Figure 3: The effect of conflict fatalities on hate crime



Note: The figure shows coefficient estimates on anti-Jewish and anti-Islamic hate crimes corresponding to columns (1) − (4) in Table 3. Estimates on anti-Black and anti-Hispanic hate crimes are also included for comparison.

a large Palestinian attack increases anti-Muslim hate crimes by 44%. Not only is the effect of smaller attacks insignificant, but the point estimates are 10 times smaller for Israeli attacks and 6 times smaller for Palestinian attacks.[22]

Assuming that there are no spillovers to other hate crime categories (McConnell and Rasul, 2021), we expect to find no effects of the conflict on hate crimes toward groups that do not have a tie to the conflict. In Figure 3 and Appendix Table A9, we find, reassuringly, that conflict fatalities do not affect anti-Black or anti-Hispanic hate crimes, the two most common hate crime categories in the United States.

Our results consistently show that it is the group associated with the attacker that is subjected to hate crimes, but we are cautious about concluding that Israeli attacks do not have an effect on anti-Islamic hate crimes. When testing against the null, we find that Israeli attacks cause anti-Jewish hate crimes and Palestinian attacks cause anti-Islamic hate crimes. We do not find any significant effects of Israeli attacks on anti-Islamic hate crimes or Palestinian attacks on anti-Jewish hate crimes. We further examine this asymmetry by testing whether (1) Israeli attacks have a greater effect on anti-Jewish hate crimes than Palestinian attacks, (2) Palestinian attacks have a greater effect on anti-Islamic hate crimes than Israeli attacks, (3) Israeli attacks have a greater effect on anti-Jewish than on anti-Islamic hate crimes and (4) Palestinian attacks have a greater effect on anti-Islamic than on anti-Jewish hate crimes. The bottom three rows of Table 3 presents the *p*-values for these equivalence tests. The tests clearly show that Palestinian attacks have a significantly greater effect on anti-Islamic than on anti-Jewish hate crimes, while we cannot reject that the effect of Israeli attacks is greater on anti-Jewish than on anti-Islamic hate crimes nor that Israeli and Palestinian attacks have significantly different effects on both categories of hate crimes. The inconclusive test results are primarily driven by the imprecise null effect of Israeli attacks on anti-Islamic hate crimes, as shown in Figure 3.

[22]In Appendix Table A8, we show that the results are virtually the same when we partition the small attack dummy into two additional categories.

5.2 The Effect of Conflict News on Hate Crime

This section examines how incidence of hate crimes changes after US mass media coverage of violence by each party in the conflict. We estimate equation (2) using as the independent variables the length of conflict coverage, the day of the attack and the previous day, on Israeli violence, Palestinian violence, and violence from both sides, respectively. The results, presented in Table 4 and Figure 4, largely mirrors those in the previous section.

Columns (1) and (2) of Table 4 regress anti-Jewish and anti-Islamic hate crimes on the length of conflict news, the day of the attack and the previous day, covering Israeli attacks, both sides attacking, or Palestinian attacks, respectively. Column (1) shows that anti-Jewish hate crimes are triggered by news coverage involving Israeli attacks, regardless of whether news reporting also covers Palestinian violence towards Israel. This is indicated by the significant effects of coverage of Israeli attacks and both sides attacking. The expected number of anti-Jewish hate crimes increases by 4.2% with one additional minute of conflict news reporting focusing exclusively on Israeli attacks, and by 3.4% with the analogous increase of reporting on attacks from both sides. In column (2), we see a large and significant effect on anti-Muslim hate crimes of news on Palestinian attacks. One additional minute of news reporting on Palestinian attacks increases expected anti-Islamic hate crimes by 11.8%. Appendix Table A10 shows results from alternative lag structures, with up to five individual lags of the independent variables. The results are largely consistent, and suggests that for most of the reporting, the most pronounced effect is news coverage the same day.

Columns (3) and (4) show that, as for fatalities, days with extensive news reporting are driving the results. We regress hate crimes on two dummies for each type of coverage, indicating whether the conflict news reporting is in or below the top percentile. On days with top percentile reporting on Israeli attacks or both sides attacking, anti-Jewish hate crimes are expected to increase by 26% and 36%, respectively, whereas top percentile reporting on Palestinian attacks leads to a 46% increase in anti-Muslim hate crimes. The point estimates of news reporting below the top percentile are much smaller and for the most part insignificant. However, reporting in the bottom 99 percentiles of both sides attacking has a significant

Table 4: News on the Israeli-Palestinian conflict and hate crimes

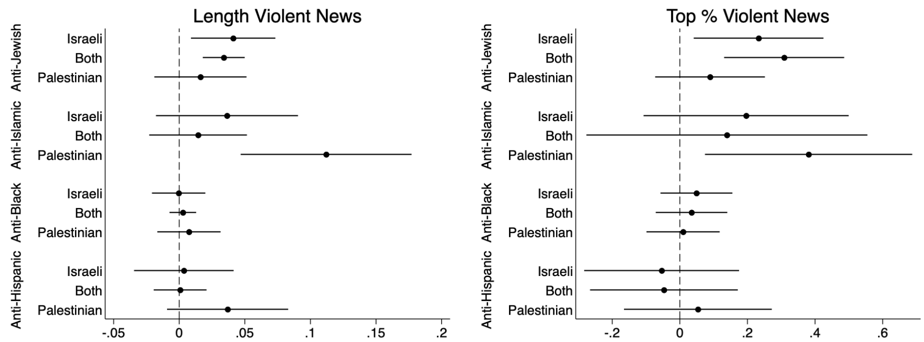
	(1) Anti-Jewish	(2) Anti-Islamic	(3) Anti-Jewish	(4) Anti-Islamic
Length of conflict news, same day and previous day, covering...				
Israeli attacks	0.041^{*}	0.036		
	(0.016)	(0.028)		
Both sides attacking	0.034^{***}	0.014		
	(0.008)	(0.019)		
Palestinian attacks	0.016	0.112^{***}		
	(0.018)	(0.033)		
Top 1% conflict news, same day and previous day, covering ...				
Israeli attacks			0.233^{*}	0.196
			(0.098)	(0.155)
Both sides attacking			0.309^{***}	0.139
			(0.091)	(0.212)
Palestinian attacks			0.089	0.381^{*}
			(0.083)	(0.156)
Bottom 99% conflict news, same day and previous day, covering ...				
Israeli attacks			−0.028	0.040
			(0.039)	(0.098)
Both sides attacking			0.096^{*}	0.104
			(0.041)	(0.091)
Palestinian attacks			−0.004	0.128
			(0.048)	(0.108)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes
Observations	5633	5633	5633	5633
Mean dependent var.	2.369	0.449	2.369	0.449
SD of dependent var.	1.843	0.729	1.843	0.729
Model	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.033	0.050	0.033	0.050
p-value $\beta_I^{Jew} = \beta_I^{Isl}$	0.834		0.750	
p-value $\beta_P^{Jew} = \beta_P^{Isl}$	0.004		0.109	
p-value $\beta_I^{k} = \beta_P^{k}$	0.237	0.039	0.199	0.367

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) and (3)) and Muslims (columns 2 and 4). The independent variables are our measures of the length of conflict-related news aggregated for day t and $t-1$ and two mutually exclusive dummy variables indicating days with less or top percentile news reporting within each type of reporting. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, presented in Section 4.1. The last three rows present the p-values of a test for equality between either the effects of (top) reporting on Israeli or Palestinian attacks on anti-Jewish and anti-Islamic hate crimes estimated using seemingly unrelated regressions, or a test of equal effects within models for Israeli and Palestinian attacks. Newey-West standard errors allowing for autocorrelation of up to seven lags are presented in parentheses.
* $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

effect on anti-Jewish hate crimes.[23] Figure 4 and Appendix Table A11 once again show that anti-Black and anti-Hispanic hate crimes are not affected by con-

[23]In Appendix Table A12, we show that these results are robust to splitting the dummy for news reporting below the top percentile into one additional category.

Figure 4: News on the Israeli-Palestinian conflict and hate crimes



Note: The left graph shows coefficient estimates corresponding to columns (1) and (2) in Table 3, with estimates on anti-Black and anti-Hispanic hate crimes included for comparison. The right graph analogously presents the coefficient estimates from columns (3) and (4) from the same table.

flict news reporting.

The results in Table 4 show that the effect of conflict news reporting on hate crimes depends on whether it focuses on Israeli or Palestinian violence, but we are once more cautious about ruling out an effect of coverage of Israeli violence on anti-Islamic hate crimes. In the bottom panel of Table 4, we perform the same equivalence tests as for fatalities, focusing on the difference between reporting on Israeli and Palestinian violence. The effect of Palestinian violence on anti-Islamic hate crimes is greater than the effect on anti-Jewish hate crimes, but we cannot reject that reporting on Israeli and Palestinian violence has equally strong effects on the two types of hate crimes nor that Israeli attacks do not have an effect on anti-Islamic hate crimes. This also appears to be driven by the imprecise null effects of Israeli attacks on anti-Islamic hate crimes.

5.3 Heterogeneity of Media Reporting and Hate Crimes

This section uses our conflict news measures to gain further insights into why the conflict causes increases in hate crimes and into the generalizability and importance of our findings. Specifically, we address four additional questions: First, do smaller attacks affect hate crimes? Second, do our findings generalize to other conflicts? Third, does nonviolent conflict reporting affect the incidence of hate crimes?

And fourth, does the conflict affect violent as well as nonviolent hate crimes?

First, we find evidence that smaller attacks, that still receive media coverage, also induce hate crimes. In Section 5.1, we found that neither Israeli or Palestinian attacks below the top percentile increased hate crimes. While such attacks might induce less animosity and thus fewer hate crimes, the reason may also be that because smaller attacks receive little media coverage, they do not reach potential hate crime perpetrators. We investigate this by regressing anti-Jewish and anti-Islamic hate crimes on our linear measures of conflict reporting while excluding days that have had an attack in the top percentile from either side sometime during the previous week. This allows us to ascertain whether small attacks that are covered in the news may trigger hate crimes. We see in column (1) of Table 5 that the effect of coverage including Israeli violence on anti-Jewish hate crimes remains and actually increases slightly compared with estimates in Table 4. The same is true for the effect of Palestinian violence on anti-Islamic hate crimes, as seen in column 3. Thus, attacks below the top percentile that receive news coverage trigger hate crimes. This does not mean, however, that we identify a causal effect of media reporting, since the effect of smaller attacks that receive extensive reporting is likely very different from the effect of smaller attacks that are ignored by the media. Thus, we cannot be sure whether what is driving the effect on hate crimes is the increased media coverage itself or the characteristics of smaller attacks that lead to increased media coverage.[24]

Second, we provide evidence that the conflict spillover we have identified for the Israeli-Palestinian conflict seems to extend to the broader Arab-Israeli conflict. Our news data contain reporting on the 2006 Israel-Lebanon war. This war, primarily between Israel and Hezbollah, a Shia Islamist political party and militant group, took place during approximately one month in 2006, and is estimated to have resulted in 1,200–1,300 Lebanese casualties and 165 Israeli casualties. Columns (2) and (4) present the effects of the Israel-Lebanon war news coverage on anti-Jewish

[24] This is also the reason that we do not include both media reporting and attacks in the same regression specification. Intuitively, one might think that including both variables in the same specification allows us to capture the effect of media reporting, controlling for the size of the attack. However, since media reporting most certainly is an outcome of the attack itself, this would introduce post-treatment bias in the estimated effect of media reporting.

and anti-Islamic hate crimes. The intensity and brevity of the war make it difficult to disentangle which side is the predominant aggressor in the individual news segments, and we therefore assess the aggregate linear effect of reporting in minutes averaged across the three news networks on both anti-Jewish and anti-Islamic hate crimes. The results show that media coverage of the Israel-Lebanon conflict increases both anti-Jewish hate crimes and anti-Islamic hate crimes. The effect on anti-Islamic hate crimes is particularly strong. One additional minute of reporting on the Israel-Lebanon conflict is expected to increase anti-Islamic hate crimes by 2.1% and anti-Jewish hate crimes by 1.5%.

Third, we find no evidence that nonviolent conflict news affects hate crimes. Our main results show that attacks and conflict reporting on violence triggers hate crimes primarily against the ethno-religious group associated with the attacker. This suggests that general conflict news has little effect on hate crimes. We test this directly by examining the effect of *nonviolent conflict news*, which measures the coverage of the Israeli-Palestine conflict excluding all reporting on violence. The results are presented in columns (2) and (4) of Table 5. We find no evidence that nonviolent news coverage of the Israeli-Palestinian conflict induces anti-Jewish or anti-Islamic hate crimes. None of the individual coefficients are significant, and both point estimates are small and negative. Thus, it appears that general conflict salience does not affect hate crimes, even though our measurement of nonviolent conflict news, in addition to reporting on peace talks and high-level political meetings, contains reporting on controversial events like settlement expansions or policy decisions affecting the conflict.

Lastly, we show that the conflict not only triggers less severe forms of hate crimes, such as property crimes and vandalism, but also increases violence toward Jews and Muslims in the United States. Anti-Jewish and anti-Islamic hate crimes cover a vast range of specific crimes that vary greatly in their severity, from crude acts of vandalism and hate speech to assault, arson, and murder. It is therefore crucial to examine what types of hate crimes are triggered by the conflict. Table 6 estimates the effects of fatal attacks and news coverage on violent and nonviolent hate crimes respectively. Columns (1) and (2) show that Israeli attacks trigger both violent and nonviolent anti-Jewish hate crimes. columns (3) – (4) show the

Table 5: Effects of different news content on hate crime

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Islamic	(4) Anti-Islamic
Length of conflict news, same day and previous day, covering...				
Israeli attacks	0.048*	0.042**	0.026	0.038
	(0.020)	(0.016)	(0.038)	(0.027)
Both sides attacking	0.055**	0.034***	0.080	0.013
	(0.021)	(0.008)	(0.045)	(0.019)
Palestinian attacks	−0.010	0.017	0.132*	0.113***
	(0.037)	(0.018)	(0.059)	(0.033)
Nonviolent events		−0.013		−0.000
		(0.019)		(0.037)
Israel-Lebanon violent conflict events		0.015*		0.021*
		(0.007)		(0.009)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes
Observations	5372	5633	5372	5633
Mean dependent var.	2.355	2.369	0.444	0.449
SD of dependent var.	1.846	1.843	0.725	0.729
Excluding week of large attacks	Yes	-	Yes	-
(Pseudo) R-squared	0.034	0.033	0.052	0.050

The dependent variables are the total number of hate crimes towards Jews (columns (1) − (2)) and Muslims (columns (3) − (4)). The first four independent variables are our measures of the length of conflict-related news aggregated for day t and $t-1$, split into type of reporting. The last measure includes only reporting on violence in the Israel-Lebanon conflict. Columns (1) and (3) estimate the model on a sample that excludes days with a top percentile attack in the previous week. All models control for year, calendar month and day of the week fixed effects, and are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

results for anti-Islamic hate crimes. Palestinian attacks trigger violent anti-Muslim hate crimes, while the coefficient for nonviolent hate crimes is smaller, less precise, and insignificant. Columns (5) − (8) of Table 6 show the analogous results for days with the most extensive news coverage. Columns (5) and (6) show that news coverage of Israeli violence or violence on both sides triggers both violent and nonviolent anti-Jewish hate crimes. However, the effect of Israeli violence on nonviolent anti-Jewish hate crimes is not significant. Reporting on Palestinian violence has a significant effect on violent anti-Muslim hate crimes, while the effect on nonviolent anti-Muslim hate crimes is significant only at the 10% level. Importantly, it is well known that hate crimes are severely underreported and that reporting differs across hate crime categories (Pezzella, Fetzer and Keller, 2019). It is plausible that underreporting is greater for less severe crimes, and, we do not rule out that the null effects on nonviolent hate crimes may be driven by differential reporting across the two communities. Specifically, as shown in Appendix Table A3, while violent hate crimes account for 30% of the reported hate crimes against Jews, they account for 66% of the reported hate crimes against Muslims. That American Muslims are subjected to more violent than nonviolent hate crimes may, of course, be true, but this finding may also be explained by underreporting of nonviolent hate crimes among American Muslims.

Table 6: Effect on violent and nonviolent hate crimes

	(1) Violent Anti-Jewish	(2) Nonviolent Anti-Jewish	(3) Violent Anti-Muslim	(4) Nonviolent Anti-Muslim	(5) Violent Anti-Jewish	(6) Nonviolent Anti-Jewish	(7) Violent Anti-Muslim	(8) Nonviolent Anti-Muslim
Number of victims, same day and previous day, from...								
Israeli attacks	0.002*	0.001*	0.001	0.000				
	(0.001)	(0.001)	(0.002)	(0.002)				
Palestinian attacks	0.007	0.004	0.036***	0.009				
	(0.009)	(0.006)	(0.011)	(0.015)				
Length of conflict news, same day and previous day, covering...								
Israeli attacks					0.050*	0.037	0.051	0.010
					(0.022)	(0.020)	(0.038)	(0.050)
Both sides attacking					0.053***	0.022*	-0.003	0.037
					(0.011)	(0.009)	(0.027)	(0.028)
Palestinian attacks					0.013	0.017	0.119**	0.100
					(0.032)	(0.025)	(0.040)	(0.056)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t + 1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5763	5763	5763	5763	5633	5633	5633	5633
Mean dependent var.	0.702	1.664	0.299	0.153	0.706	1.663	0.297	0.152
SD of dependent var.	0.930	1.529	0.580	0.415	0.933	1.528	0.578	0.413
Model	NB ML	NB ML	NB ML	NB ML	NB ML	NB ML	NB ML	NB ML
Pseudo R-squared	0.041	0.024	0.054	0.047	0.041	0.025	0.052	0.047

Notes: The dependent variables are violent (columns (1) and (5)) and nonviolent (columns (2) and (6)) anti-Jewish hate crimes, and violent (columns (3) and (7)) and nonviolent (columns (4) and (8)) anti-Muslim hate crimes. The independent variables are dummies for days with top percentile Israeli attacks, top percentile Palestinian attacks or top percentile conflict news reporting.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 Sensitivity Analysis

This section examines the sensitivity of our main results, focusing on the effects of top percentile attacks and news reporting. We begin by examining if the generalizability of our results limited. Two sensitivity checks suggest that our results are not driven by a few extreme and temporally concentrated events and days. First, the results are not sensitive to dropping important US states from the sample. Appendix Table A16 estimates our main models of conflict fatalities and conflict news on hate crime, while excluding hate crimes in California, New York, or New Jersey from the sample. These three states have the highest number of anti-Jewish and anti-Islamic hate crimes in our sample. Panel A shows that the effects of Israeli attacks on anti-Jewish hate crimes and of Palestinian attacks on anti-Islamic hate crimes, are robust to excluding hate crimes occurring in these states. Panel B shows the analogous results for the effect of top conflict news reporting. For anti-Jewish hate crimes, the estimates for reporting on Israeli violence are smaller and become insignificant when dropping either California or New York, but the effect of reporting on violence from both sides remains significant. The results for anti-Islamic hate crimes are less sensitive to dropping either of these states.

Second, the main results are not driven by a single conflict period in our sample, but there may be heterogeneity in the effect sizes across conflict periods. Appendix Table A14 splits the sample into four particularly intense conflict periods and estimates the effects of conflict fatalities and conflict news the same day and the previous day on hate crimes. The conflict periods are the Second Intifada, Operation Cast Lead, Operation Pillar of Defense, and Operation Protective Edge, described in Section 3.2. In the models, we exclude one conflict period at a time. Panel A shows the effect of the largest Israeli and Palestinian attacks on anti-Jewish and anti-Islamic hate crimes. Both the effects of Israeli and Palestinian attacks remain significant when we drop the individual conflict periods, but the point estimates show some variation. For instance, excluding Operation Protective Edge, accounting for 25% of all fatalities from Israeli attacks, reduces the point estimates and precision somewhat. Dropping the Second Intifada, accounting for 75% of fatalities from Palestinian attacks, decreases the precision of the estimate of Palestinian attacks but increases the point estimates substantially. Panel B shows the effect of top percentile reporting on violence from Israeli, Palestinian, or both sides, respectively. These results are more sensitive to excluding the Second Intifada compared with the effect of fatalities, but the effects are largely unchanged by dropping the other conflict periods. This is not surprising, since the Second Intifada accounts for 62% of all conflict coverage. Dropping the Second Intifada reduces the precision for all types of news reporting that are significant in the main analysis and also reduces the point estimates for Israeli violence and violence from both sides. In contrast, the coefficient estimate for reporting on violence from both sides increases substantially for anti-Islamic hate crimes. This may reflect that most of the extensive news reporting exclusively covering Palestinian violence occurs during this period, and that Palestinian attacks after the Second Intifada occur primarily in conjunction with Israeli attacks. In Appendix Table A15, we provide an alternative measure of conflict news by collapsing the violent conflict reporting variables into one variable, and regress hate crimes on days with top percentile overall reporting on conflict violence. We see a consistent effect of violent conflict reporting on both anti-Jewish and anti-Islamic hate crimes, although the effect on anti-Islamic hate crimes is significant only at the 10% level when dropping either the Second Intifada or Protective Edge.

We next turn to the examining the plausibility of the identifying assumptions and the sensitivity of the main results to alternative model specifications and subsamples. In sum, the results are largely unaffected by (1) the choice of temporal controls, lag structure, and model specification, (2) subsetting the analysis to police agencies with consistent participation in the Uniform Crime Reporting Program, (3) adding future attacks and reporting to the model, and (4) controlling for jihadist Western attacks targeting Americans.

First, the main results are not dependent on including a specific set of control variables. In columns (1) – (10) of Appendix Table A13, we show that the results are very stable when adding one set of temporal controls at a time. This implies, for instance, that Israeli attacks strategically timed to US news cycles and events are unlikely to affect our results. Column (11), in both panels, shows that our estimates are relatively unaffected when adding two lags of the dependent variable.[25] An

[25]We choose two lags because this obtains the lowest Bayesian information criterion (BIC) test

additional potential concern is that jihadist terrorist attacks targeted against US citizens could bias our estimates, if these affect both hate crimes in the United States and the timing of, for example, Israeli attacks. Ivandic, Kirchmaier and Machin (2019), for instance, show that jihadist terror in Europe and the United States affects hate crimes in the UK. We address this by controlling for whether there was a jihadist attack in a Western country with US fatalities in the past five days. The terrorist attacks are obtained from the Global Terrorist Database and are listed in Appendix Table A6 (LaFree and Dugan, 2007). In column (12) in both panels of Appendix Table A13, we show that our estimates are unaffected by this.[26]

Second, our results are robust to alternative model specifications, such as Ordinary Least Squares (OLS) or probit regression. Appendix Table A17 estimates our main specifications using OLS on the number of hate crimes and log(+1) of the number of hate crimes, respectively, as well as probit regression on an indicator variable for the incidence of anti-Jewish or anti-Islamic hate crimes on that day. Presented in columns (3) – (6) in both panels, the OLS models show results similar to our main results, given in the first two columns for comparison. In the last two columns of both panels we present the results from the probit regression with a collapsed dependent variable. For anti-Jewish hate crimes, estimates are no longer significant for either attacks or reporting. These insignificant results appear to be driven by a ceiling effect, as approximately 86% of our days in the sample have at least one reported incidence of anti-Jewish hate crime. In the last column, we find a significant effect of large Palestinian attacks on anti-Islamic hate crimes and a smaller and nonsignificant effect of coverage of Palestinian attacks.

Third, results in Appendix Table A18 shows that the main results are not dependent on a specific lag structure. We estimate our main linear specifications using either weekly level data (columns (1) – (4)) or daily level data, but with our

statistic. We also estimate the main models with up to 10 lags, which entirely eliminates residual autocorrelation. Main estimates, not included in the article, are virtually unchanged. We also ascertained that the residual of the main models are stationary using an augmented Dickey-Fuller test.

[26]In a separate analysis, which is not included in the article but can be obtained upon request, we find similar results to those of Ivandic, Kirchmaier and Machin (2019) but in the US context: jihadist terrorist attacks with US victims (excluding 9/11) trigger hate crimes against American Muslims the following days, even if this attack takes place in a different western country.

independent variables aggregated the past three days instead of two days (columns (5) – (8)). The table shows largely the same results as in our main estimates. Conflict news is consistently increasing both anti-Jewish and anti-Muslim hate crimes. Israeli attacks seem to primarily trigger anti-Jewish hate crimes, while Palestinian attacks seem to primarily trigger anti-Muslim hate crimes, although the coefficient estimate decreases somewhat and becomes insignificant in the daily level data with three-day aggregates.

Fourth, an additional threat to our empirical strategy would be if agencies select in and out of the Uniform Crime Reporting Program in response to events in the conflict. Appendix Table A19 replicates our main specifications using only data from agencies that did not drop out of the program once they started participating. Our findings replicate on this sample, and are, if anything, more pronounced compared with the full sample.

Finally, Appendix Tables A20-A21 shows that the main results are relatively unaffected when including future large attacks and media reporting in the models.[27]

5.5 Retaliatory Motive or Conflict Salience?

The overall results are consistent with perpetrators being driven by a retaliatory motive. However, since we do not have data on who the perpetrators are, and, since motives cannot be observed, we cannot completely rule out all alternative explanations for why the conflict triggers hate crimes. That said, two of our results are inconsistent with alternative explanations. First, we repeatedly find that it is the group associated with the attacker that is subjected to hate crimes. These asymmetric effects, reported in Sections 5.1 and 5.2, show that conflict violence

[27] This is despite the fact that including leads can be expected to attenuate the estimated effect. For example, consider a model with an underlying latent independent variable, denoted *contentious conflict events reaching potential hate crime offenders*, which (1) triggers hate crimes, (2) is measured with error via fatal attacks or news reporting, and (3) generates future attacks and news reporting. In this case, measurement error in the independent variables will cause attenuation bias, which will be further exacerbated when controlling for future attacks or reporting, since, because of the correlation between contentious conflict events and future attacks, this is equivalent to partially controlling for the contentious conflict events themselves, leading to overcontrol bias (Cinelli, Forney and Pearl, 2020). As put by Angrist and Pischke (2008), they are “bad controls”.

in general does not trigger hate crimes. Although we do not find that the effect of Israeli attacks and reporting on Israeli violence is significantly different across anti-Jewish and anti-Islamic hate crimes, we find significant effects of attacks only on the religious group associated with the attacker. Second, general salience of the Israeli-Palestinian conflict does not trigger hate crimes. This is evident by the insignificant effect of nonviolent conflict news, reported in Section 5.3. Together, these emphasize the importance of the type of conflict event or the content of news reporting as opposed to the general intensity of fighting or reporting for what group is subjected to hate crimes. The asymmetric effects suggest that perpetrators are attached to the conflict actors, and that violence directed towards these actors triggers a retaliatory motive.

6 Concluding Remarks

We document that social identity ties can facilitate the spread of violent conflict through increasing animosity. Using daily data on fatalities and US news coverage of the Israeli-Palestinian conflict between 2000 and 2016, we examine whether the conflict causes hate crime towards Jews and Muslims in the United States. We find the same pattern in conflict spillovers using both conflict measures: anti-Jewish hate crimes increase after Israeli attacks, and anti-Islamic hate crimes increase after Palestinian attacks. We find no effect of nonviolent news reporting on hate crimes, nor do we find that the ethno-religious group not associated with the attacker is subjected to hate crimes. Together, the findings indicate that conflict events trigger a retaliatory motive against the ethno-religious group associated with the attacker, inducing violent behavior by perpetrators of hate crime against American Jews and Muslims. While news reporting in both the United States and Europe has indicated that the Israeli-Palestinian conflict may trigger anti-Jewish hate crimes, until recently, there has been little reporting on how the conflict affects Muslims living outside of the conflict vicinity.[28] Our findings, however, show

[28]See "'Death to Palestine' spray painted on Brooklyn mosque", ABC7 NY, May 13, 2021, and "Antisemitic incidents heightened across US amid Israel-Gaza fighting; mosques were damaged, too", NBC News, May 21, 2021.

that the conflict has triggered hate crimes against both Jews and Muslims at least since 2000.

Animosity triggered through social identity ties may play an even larger role in the transmission of violence in settings at risk of civil conflict or larger-scale violence. This is partly because animosity directed at groups with identity ties to foreign conflict actors are likely to amplify other channels through which conflicts might spill over. Consider the example of the Rwandan Civil War spreading into neighboring countries in the aftermath of the genocide toward the Tutsi population in 1994. In 1995, exiled Hutu extremists in the neighboring Democratic Republic of the Congo (then Zaire) engaged in violent campaigns against the local Zairean Tutsies, recruiting Zairean Hutus to engage in ethnic violence and essentially continue the genocide. The spread of this ethnic conflict had many causes, including the cross-border flow of refugees, weapons, and resources, as well as Zairean Hutus being inspired by their Rwandan coethnics to engage in violence toward local Tutsis for political reasons, among others (e.g., Stearns, 2012; Gourevitch, 2015). To what extent did the Rwandan Civil War spur cross-border animosity toward Zairean Tutsis that *facilitated* the recruitment of local Hutus in these genocidal campaigns? An important endeavor for further research is to understand how and under what conditions the spread of intergroup animosity results in conflict contagion.

The cross-border spread of animosity through identity ties could also have important ramifications beyond violent and criminal behavior. For example, it might cause intergroup trust to deteriorate and, as a result, adversely affect trade relationships with non-negligible economic costs. In recent work, Korovkin and Makarin (2019) show that the trade relationships between Ukraine and Russia clearly deteriorated in response to the 2014 Russia-Ukraine conflict even in areas not directly affected by combat. Other research shows that intergroup conflict can increase the salience of social identities (Shayo, 2020), thereby affecting behavior, such as court orders (Shayo and Zussman, 2011) and consumption patterns (Atkin, Colson-Sihra and Shayo, 2021). Animosity directed toward a particular minority can also have long-term effects on the group's rate of assimilation, labor market participation, and ethnic identification (Gould and Klor, 2016). Mitts (2019) provide an extreme example where anti-Muslim hostility in Europe might have increased Muslim radicalization and support for ISIS. Research also shows that propaganda in conflict contexts may effectively promote ethnic violence (DellaVigna et al., 2014; Yanagizawa-Drott, 2014). However, we know little about how the framing of violent conflict in mass media might cause violent spillovers. An important future research agenda is whether the extent and type of mass media reporting are significant for the spread of violence. This is perhaps especially important for largely unmoderated social media content, suggested to have fueled intergroup animosity and violence in, for example, Myanmar and the Philippines.

We show that violent conflict spillovers and victimization can transcend the conflict locality. As news and social media reporting become ever more rapid, individuals all over the globe can take part in conflict development in real time. With increasing migration and technological advancement, the consequences of regional conflicts may also spread and become less bound to the conflict vicinity.

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7 Appendix

Table A1: Seasonal variation in hate crimes, conflict victims and conflict news in 2000 – 2016, excluding six months following the 9/11 attacks

	Hate crime				Victims				Conflict News					
	Anti-Jewish		Anti-Islamic		Palestinian attacks		Israeli attacks		Any	Total	Israeli attacks	Both attacking	Palestinian attacks	No violence
	Obs. (1)	Share (2)	Obs. (3)	Share (4)	Obs. (5)	Share (6)	Obs. (7)	Share (8)	Share (9)	Min./day (10)	Min./day (11)	Min./day (12)	Min./day (13)	Min./day (14)
Total	13652	1	2606	1	1111	1	9038	1	0.15	0.24	0.05	0.09	0.04	0.06
Day of the week														
Monday	2194	0.16	365	0.14	116	0.10	1118	0.12	0.15	0.23	0.05	0.09	0.03	0.05
Tuesday	2030	0.15	342	0.13	200	0.18	1318	0.15	0.14	0.22	0.05	0.08	0.04	0.05
Wednesday	1904	0.14	384	0.15	204	0.18	1337	0.15	0.14	0.21	0.05	0.08	0.04	0.04
Thursday	1995	0.15	373	0.14	181	0.16	1351	0.15	0.14	0.22	0.04	0.07	0.05	0.06
Friday	2168	0.16	407	0.16	138	0.12	1284	0.14	0.14	0.20	0.03	0.08	0.03	0.06
Saturday	1661	0.12	380	0.15	102	0.09	1432	0.16	0.17	0.29	0.09	0.09	0.03	0.07
Sunday	1700	0.12	355	0.14	170	0.15	1198	0.13	0.21	0.36	0.07	0.14	0.05	0.11
Month of the year														
January	968	0.07	158	0.06	68	0, 06	1298	0, 14	0.16	0.25	0.07	0.05	0.02	0.10
Febraury	881	0.06	139	0.05	45	0, 04	314	0, 03	0.11	0.10	0.01	0.00	0.02	0.07
March	1203	0.09	217	0.08	189	0, 17	666	0, 07	0.18	0.29	0.06	0.11	0.06	0.05
April	1428	0.10	234	0.09	83	0, 07	554	0, 06	0.14	0.42	0.09	0.20	0.05	0.08
May	1268	0.09	247	0.09	84	0, 08	435	0, 05	0.17	0.22	0.05	0.04	0.06	0.06
June	1113	0.08	209	0.08	136	0, 12	342	0, 04	0.20	0.27	0.05	0.07	0.05	0.09
July	963	0.07	241	0.09	117	0, 11	2041	0, 23	0.21	0.36	0.08	0.20	0.03	0.05
August	1103	0.08	221	0.08	95	0, 09	932	0, 10	0.19	0.27	0.06	0.07	0.05	0.08
September	1083	0.08	279	0.11	59	0, 05	350	0, 04	0.13	0.14	0.03	0.04	0.01	0.05
October	1349	0.10	216	0.08	90	0, 08	604	0, 07	0.14	0.27	0.06	0.14	0.04	0.04
November	1241	0.09	224	0.09	98	0, 09	666	0, 07	0.15	0.22	0.04	0.09	0.04	0.05
December	1052	0.08	221	0.08	47	0, 04	836	0, 09	0.10	0.13	0.04	0.04	0.01	0.04

Note: Hate crime data from FBI (2018), data on fatalities from *B'Tselem* and data on conflict news from *Vanderbilt Television News Archive*. The exact sample period is September 29, 2000, to September 10, 2001, and March 1, 2002, to December 31, 2016. The table shows seasonal variation over month of the year and day of the week for anti-Jewish and anti-Islamic hate crime incidents, Israeli and Palestinian victims, and conflict news on ABC, CBS, and NBC. For hate crime and victim data, *observation (obs.)* refers to the number of incidents and victims, and *share* refers to the share of incidents or victims on a given day of the week or month. The first conflict news column shows the share of day or month with any conflict news reporting. The second conflict news column shows the average length of conflict news on the three networks, and the last four columns split the conflict news variable into four categories, explained further in Section 3.3.

Table A2: Descriptive statistics

	Source	Mean	SD	Min	Max
Victims from Israeli attacks	B'Tselem	1.57	9.17	0	356
Victims from Palestinian attacks	B'Tselem	0.19	1.20	0	27
Top 1% Palestinian attack (dummy)	B'Tselem	0.01	0.09	0	1
Top 1% Israeli attack (dummy)	B'Tselem	0.01	0.10	0	1
Conflict reporting on Israeli violence (min.)	Vanderbilt News Archive	0.05	0.35	0	8
Conflict reporting on Israeli and Palestinian violence (min.)	Vanderbilt News Archive	0.09	0.56	0	10
Conflict reporting on Palestinian violence (min.)	Vanderbilt News Archive	0.04	0.28	0	5
Conflict reporting on nonviolent events (min.)	Vanderbilt News Archive	0.06	0.34	0	6
Top 1% conflict reporting on Israeli violence (dummy)	Vanderbilt News Archive	0.01	0.10	0	1
Top 1% conflict reporting on Israeli and Palestinian violence (dummy)	Vanderbilt News Archive	0.01	0.10	0	1
Top 1% conflict reporting on Palestinian violence (dummy)	Vanderbilt News Archive	0.01	0.10	0	1
Top 1% conflict reporting on Israeli violence (dummy)	Vanderbilt News Archive	0.01	0.10	0	1
News pressure (10 min.)	Vanderbilt News Archive	0.88	0.25	0	3
Anti-Jewish hate crimes	Uniform Crime Reports	2.37	1.84	0	20
Anti-Islamic hate crimes	Uniform Crime Reports	0.45	0.73	0	6
Anti-Black hate crimes	Uniform Crime Reports	6.35	3.00	0	22
Anti-Hispanic hate crimes	Uniform Crime Reports	1.25	1.22	0	10
Observations		5767			

Note: Measures on conflict reporting are defined as the average length in minutes, per recorded evening news broadcast on ABC, CBS, and NBC, of conflict-related stories that mentioned Israeli violence, violence on both sides, Palestinian violence, or no violence. The top percentile dummies for either victims or conflict reporting are indicators for the percentage of days in the sample with the most fatalities or news reporting in the relevant category. News pressure is defined as the length devoted to the top three news stories unrelated to Israel or Palestine in the evening newscast on ABC, CBS, and NBC, following Eisensee and Strömberg (2007). If there are news stories related to either Israel or Palestine, we define news pressure as the time allotted to the top three stories unrelated to Israel and Palestine divided by the time allotted to all other stories unrelated to Israel and Palestine. This is then multiplied by the length of the broadcast to get news pressure in minutes.

Table A3: Hate crimes against Jews and Muslims in 2000 – 2016, excluding six months after 9/11

	Anti-Jewish		Anti-Islamic	
	Obs.	Share	Obs.	Share
Most common locations				
Residence/home	3997	0.29	567	0.22
School/college	1794	0.13	150	0.06
Church/synagogue/temple	1077	0.08	317	0.12
Highway/road/alley	1054	0.08	343	0.13
Other/unknown	5730	0.42	1229	0.47
Most common offense types				
Destruction of property/vandalism	9310	0.68	766	0.29
Intimidation	2916	0.21	944	0.36
Simple assault	807	0.06	522	0.20
Aggravated assault	175	0.01	191	0.07
Other	444	0.03	183	0.07
Most common offense states				
New York	3532	0.26	270	0.10
New Jersey	2855	0.21	187	0.07
California	2075	0.15	339	0.13
Massachusetts	804	0.06	161	0.06
Michigan	234	0.02	286	0.11
Ohio	164	0.01	117	0.04
Other	3988	0.29	1246	0.48
Level of violence				
Violent hate crimes	4049	0.30	1724	0.66
Nonviolent hate crimes	9603	0.70	882	0.34

Note: Data from the FBI (2018). The table shows the most common locations, the most common offense types, the most common offense states, and the level of violence for anti-Jewish and anti-Islamic hate crime incidents. Violent hate crimes include the following categories: aggravated assault, murder/non-negligent manslaughter, negligent manslaughter, statutory rape, forcible fondling, forcible rape, forcible sodomy, intimidation, arson, kidnapping/abduction, sexual assault with an object, simple assault, and robbery. This loosely follows the definition of "crime of violence" used by United States Sentencing Commission (2018). *Observations (obs.)* refers to the number of anti-Jewish and anti-Islamic hate crimes. *Share* refers to the share of hate crimes within the hate crime category. The exact sample period is September 29, 2000, to September 10, 2001, and March 1, 2002, to December 31, 2016.

Table A4: Examples of news stories on the Israeli-Palestinian conflict

Headline	Summary	Length	Order of appearance in broadcast	Network	Included	Filter	Coding
Middle East / **Israel** and Lebanon / violence	(Studio: Charles Gibson) The effort to get more U.N. peacekeeping troops into southern Lebanon reported; scenes shown of French troops arriving.	20 sec.	6	ABC	No	Only Israel	N/A
Middle East / **Palestinians** / factional violence	(**West Bank:** Tom Aspell) The power struggle among rival **Palestinian** factions updated; scenes shown of a **Hamas** victory parade in **Gaza** and **Fatah** militiamen trashing **Hamas** offices in the **West Bank**.	70 sec.	3	NBC	No	Only Palestine	No violence between groups
Middle East / **Israelis** vs. **Palestinians** / violence	(Jerusalem: Gillian Findlay) **Israel's** calling off of cease-fire talks about another suicide bombing in Jerusalem featured; scenes shown from the bombing site in the street and of victims on the hospital; details given of **Palestinian** Authority president Yasir Arafat condemnation of today's attack.	130 sec.	4	ABC	Yes	Both in headline	Palestinian violence
Middle East violence / **Israeli** attacks	(Tel Aviv: David Hawkins) **Israeli** attacks against **Palestinian** targets in the **West Bank** and **Gaza** in retaliation for a wave of terrorist attacks reported; scenes shown on the bomb attack sites and air strikes ordered by **Israeli** prime minister Ariel Sharon against the **Palestinian** Authority.	130 sec.	2	ABC	Yes	Israel in headline, Palestine in abstract	Israeli and Palestinian violence
Middle East / **West Bank** / Jenin	(Tel Aviv: Mark Phillips) The "second battle" of Jenin, **West Bank**, to determine what happened during the **Israeli** attack on the **Palestinian** refugee camp, featured; scenes shown of the damages; details given of the contrasting versions of what happened. (Assistant Secretary of State Williams Burns - says we are seeing a human tragedy.) **Palestinian** minister Ziad Abu Zayyad - cites the need for an international peacekeeping force. **Israeli** government spokesman Mark Sofer - comments on casualty rumors.)	150 sec.	4	CBS	Yes	Palestine in headline, Israel in abstract	Israeli violence

Note: Data from *Vanderbilt Television News Archive*. The table illustrates how news on the Israeli-Palestinian conflict is filtered out from all news stories that appear on the 30 minute evening news on ABC, CBS, or NBC. Each row shows information provided by VTNA on five different news stories. We look for stories including the words Israel, Jerusalem, Tel Aviv, Palestine, Gaza, West Bank, or Hamas or any words with related roots. However, to be included in our sample of stories, at least one of the following three conditions must apply: (1) the headline contains both an Israeli and a Palestinian reference, (2) the headline contains an Israeli reference and the summary a Palestinian reference, or (3) the headline contains a Palestinian reference and the summary an Israeli reference. Rows (1) and (2) are examples of stories that are filtered out, and rows (3) – (5) are examples of stories that are included based on the three word filters.

Table A5: Holidays and events included as controls

	Holidays and events
Jewish and Israeli	Chanukah, Lag BaOmer, Leil Selichot, Pesach, Pesach Sheni, Purim, Purim Katan, Rosh Hashana, Shavuot, Shmini Atzeret, Shushan Purim, Simchat Torah, Sukkot, Tish'a B'Av, Tu B'Av, Tu BiShvat, Yom Kippur, Yom HaShoah, Yom Ha'atzmaut/Israeli Independence Day, Yom Hazikaron/Israel's Memorial Day
Islamic and Palestinian	Eid al-Adha, Muharram, the Prophet's Birthday, Isra and Mi'raj, Ramadan, Lailat al-Qadr, Eid al-Fitr, Al Nakba Day
Christian	Epiphany, Ash Wednesday, Palm Sunday, Maundy Thursday, Holy Saturday, Easter Sunday, Easter Monday, Ascension Day, Pentecost, Whit Monday, Trinity Sunday, Corpus Christi, Assumption of Mary, Feast of St Francis of Assisi, All Saints' Day, All Souls' Day, First Sunday of Advent, Feast of the Immaculate Conception, Christmas Eve
Federal	New Year's Day, Martin Luther King Jr. Day, Presidents' Day, Memorial Day, Independence Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving Day, Christmas Day
Major events	General election, Congress start session, main party national conventions, special congressional elections, gubernatorial elections, presidential inauguration, state primaries, presidential caucuses, special Senate elections, Iowa caucuses, other presidential primaries, other presidential caucuses, statewide elections, State of the Union address, Super Tuesday, New Hampshire presidential primary, FIFA World Cup, FIFA World Cup Final

Note: The table shows all holidays and events included as control variables. To select the predictable political events for our period, we use historical snapshots in the digital archive Wayback Machine (http://www.archive.com/web/) of a forward-looking US political calendar (http://www.politics1.com/calendar.htm). We also collected dates of major sport events, in both the United States and the world. We then regress our news pressure variable on dummies for these events and use the results to select a net list of events that drive news pressure in the United States. This method broadly follows the method used by Durante and Zhuravskaya (2018) and unsurprisingly leads to a similar set of events in our sample. We refer the reader to their paper for further details on this selection method. The selection of holidays is described in Section 4.1.

Table A6: Jihadist terrorist attacks targeting US citizens in 2000 – 2016, excluding six months after 9/11

Country	City	Date	Fatalities	US fatalities	Wounded
United States	Tampa	05jan2002	1	0	0
United States	Little Rock	01jun2009	1	1	1
United States	Killeen	05nov2009	13	13	32
Germany	Frankfurt	02mar2011	2	2	2
United States	Boston	15apr2013	3	2	264
United States	Cambridge	18apr2013	1	1	0
United States	Watertown	19apr2013	2	1	16
United States	Seattle	27apr2014	1	1	0
United States	Seattle	01jun2014	2	2	0
United States	West Orange	25jun2014	1	1	0
United States	New York City	23oct2014	1	1	3
United States	Morganton	18dec2014	1	1	0
United States	Chapel Hill	10feb2015	3	3	0
United States	Garland	03may2015	2	2	1
United States	Chattanooga	16jul2015	6	6	2
United States	Merced	04nov2015	1	1	4
United States	San Bernardino	02dec2015	16	15	17
United States	Columbus	11feb2016	1	1	4
Belgium	Zaventem	22mar2016	18	4	135
United States	Orlando	12jun2016	50	44	53
France	Nice	14jul2016	87	3	433
United States	St. Cloud	17sep2016	1	1	10
United States	Columbus	28nov2016	1	0	11
United States	Fort Lauderdale	06jan2017	5	5	6
United States	Denver	31jan2017	1	1	0
United Kingdom	London	22mar2017	6	1	50
United States	Tampa	19may2017	2	2	0
United States	Portland	26may2017	2	2	1
United States	New York City	31oct2017	8	2	13

Note: Data have been filtered out from the Global Terrorist Database (GTD) (LaFree and Dugan, 2007). We include attacks that are clearly motivated by jihadist or Muslim extremism according to GTD, and that either took place in the United States or had US fatalities but took place in another Western country.

Table A7: The effect of conflict fatalities on hate crime

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Islamic	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic
Victims Israeli attacks day...								
(t)	0.002	0.001	0.000	-0.000	0.004	0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
($t-1$)		0.003**	0.002**	0.002*		-0.002	-0.003	-0.003
		(0.001)	(0.001)	(0.001)		(0.002)	(0.003)	(0.003)
($t-2$)			0.002	0.001			0.003**	0.003**
			(0.002)	(0.001)			(0.001)	(0.001)
($t-3$)				0.001				-0.005
				(0.001)				(0.003)
($t-4$)				0.001				0.003
				(0.001)				(0.002)
($t-5$)				-0.001				0.000
				(0.001)				(0.002)
Victims Palestinian attacks day...								
(t)	0.005	0.004	0.003	0.004	0.008	0.005	0.003	0.003
	(0.007)	(0.007)	(0.008)	(0.007)	(0.017)	(0.017)	(0.017)	(0.018)
($t-1$)		0.006	0.006	0.005		0.043***	0.044***	0.042***
		(0.007)	(0.007)	(0.007)		(0.012)	(0.012)	(0.012)
($t-2$)			0.000	0.000			-0.015	-0.018
			(0.007)	(0.007)			(0.018)	(0.019)
($t-3$)				-0.002				0.010
				(0.006)				(0.020)
($t-4$)				0.003				0.034*
				(0.007)				(0.014)
($t-5$)				0.009				0.004
				(0.007)				(0.012)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5765	5763	5761	5755	5765	5763	5761	5755
(Pseudo) R-squared	0.031	0.031	0.031	0.031	0.050	0.051	0.051	0.052
Mean dependent var.	2.368	2.366	2.365	2.364	0.452	0.452	0.451	0.451
SD of dependent var.	1.845	1.843	1.843	1.841	0.732	0.732	0.732	0.732
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
F-test Isr. attacks (p-value)	0.112	0.015	0.006	0.007	0.119	0.301	0.010	0.041
F-test Pal. attacks (p-value)	0.472	0.568	0.826	0.839	0.641	0.001	0.002	0.000

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) – (4)) and Muslims (columns (5) – (8)). In columns (1) and (5), the independent variables are the total number of victims from an attack from the respective side at day t. Subsequent columns add up to five lags of the independent variables, where columns (4) and (8) include the total fatalities from attacks from the respective sides at t to $t-5$. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Nonlinear effects of conflict fatalities on hate crime and conflict news

	(1) Anti-Jewish	(2) Anti-Islamic	(3) Any news	(4) Length of news	(5) Israeli violence	(6) Both violence	(7) Palestinian violence
Israeli attacks (t and $t-1$)							
1 victim	0.037	−0.079	0.016	0.006	0.002	−0.005	0.017*
(percentiles: [52,67], 925 dates)	(0.030)	(0.066)	(0.012)	(0.022)	(0.007)	(0.011)	(0.008)
2 − 6 victims	0.034	0.162**	0.060***	0.065*	0.038**	0.022	0.014
(percentiles: (67,90], 1400 dates)	(0.028)	(0.061)	(0.014)	(0.032)	(0.012)	(0.020)	(0.009)
7 − 10 victims	−0.039	−0.056	0.139***	0.115	0.009	0.115	−0.014
(percentiles: (90,95], 238 dates)	(0.048)	(0.125)	(0.033)	(0.092)	(0.025)	(0.064)	(0.030)
11 − 38 victims	0.048	0.167	0.340***	0.829***	0.365***	0.581***	−0.085*
(percentiles: (95,99], 217 dates)	(0.054)	(0.128)	(0.043)	(0.180)	(0.081)	(0.135)	(0.034)
> 38 victims	0.347***	0.242	0.742***	3.392***	1.149***	2.099***	−0.052
(percentiles: (99,100], 59 dates)	(0.094)	(0.212)	(0.052)	(0.517)	(0.251)	(0.466)	(0.066)
Palestinian attacks (t and $t-1$)							
1 victim	0.039	0.021	0.012	0.078	0.095*	0.038	0.010
(percentiles: [87,93), 371 dates)	(0.042)	(0.096)	(0.024)	(0.062)	(0.048)	(0.042)	(0.013)
2 victims	0.005	−0.071	0.073	0.093	−0.049	0.123	0.031
(percentiles: [93,95], 136 dates)	(0.071)	(0.129)	(0.044)	(0.128)	(0.046)	(0.109)	(0.021)
3 − 10 victims	0.047	0.183	0.275***	0.643***	0.006	0.227*	0.427***
(percentiles: (95,99], 205 dates)	(0.053)	(0.136)	(0.044)	(0.167)	(0.060)	(0.107)	(0.074)
> 11 victims	0.057	0.423**	0.451***	2.100***	−0.204*	1.069***	1.349***
(percentiles: [99,100), 49 dates)	(0.079)	(0.156)	(0.047)	(0.273)	(0.083)	(0.236)	(0.245)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5765	5765	5700	5700	5700	5700	5700
Mean dependent var.	2.368	0.452	0.156	0.247	0.054	0.090	0.038
SD of dependent var.	1.845	0.732	0.363	0.894	0.354	0.559	0.281
Model	ML NB	ML NB	OLS	OLS	OLS	OLS	OLS
(Pseudo) R-squared	0.032	0.052	0.324	0.405	0.180	0.315	0.308
F-test Palestinian attacks	0.792	0.052	0.000	0.000	0.061	0.000	0.000
F-test Israeli attacks	0.003	0.036	0.000	0.000	0.000	0.000	0.056

Note: The independent variables are victims from Israeli and Palestinian attacks day t and $t-1$ categorized by mutually exclusive percentile dummy variables within each group. For victims of Israeli attacks, the first variable indicates dates with a fatal attack with one victim the last two days, representing the 52nd to 67th percentiles of Israeli attack dates and a total of 925 dates in our sample. The rest of the variables are specified analogously in the table. In columns (1) and (2), the dependent variables are the total number of hate crimes toward Jews and Muslims, respectively. In column (3), the independent variable is a dummy for any conflict news. Column (4) uses as the independent variable the length of conflict news, while columns (5) − (7) use conflict reporting focusing on Israeli violence, violence from both sides, or Palestinian violence, respectively. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. Columns (1) and (2) are estimated using a maximum-likelihood negative binomial model. Columns (3) − (7) are estimated using OLS. Newey-West standard errors allowing for autocorrelation of up to seven lags are presented in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: The effect of conflict fatalities on placebo hate crime categories

	(1) Anti-Black	(2) Anti-Hispanic	(3) Anti-Black	(4) Anti-Hispanic
Length of conflict news, same day and previous day, covering...				
Israeli attacks	−0.000	0.004		
	(0.010)	(0.019)		
Both sides attacking	0.003	0.001		
	(0.005)	(0.010)		
Palestinian attacks	0.007	0.037		
	(0.012)	(0.024)		
Top 1% conflict news, same day and previous day, covering ...				
Israeli attacks			0.049	−0.054
			(0.054)	(0.117)
Both sides attacking			0.035	−0.047
			(0.054)	(0.112)
Palestinian attacks			0.010	0.053
			(0.055)	(0.112)
Bottom 99% conflict news, same day and previous day, covering ...				
Israeli attacks			0.002	0.041
			(0.023)	(0.058)
Both sides attacking			−0.007	−0.012
			(0.022)	(0.049)
Palestinian attacks			−0.009	0.079
			(0.024)	(0.060)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure (t and t+1)	Yes	Yes	Yes	Yes
Observations	5633	5633	5633	5633
Mean dependent var.	6.364	1.249	6.364	1.249
SD of dependent var.	3.001	1.219	3.001	1.219
Model	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.057	0.032	0.057	0.032

Note: The dependent variables are the total number of hate crimes towards Blacks (columns (1) and (3)) and Hispanics (columns (2) and (4)). The independent variables are the total number of victims the past two days from Israeli attacks and Palestinian attacks (columns (1) and (2)) and dummy variables indicating top percentile attacks and smaller attacks for each side (columns (3) and (4)). All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: The effect of conflict news on hate crime: Lag specification

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Islamic	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic
Coverage of Israeli attacks day...								
(t)	0.075**	0.055*	0.053*	0.048	0.063	0.038	0.041	0.027
	(0.023)	(0.026)	(0.026)	(0.028)	(0.048)	(0.057)	(0.057)	(0.059)
($t-1$)		0.027	0.011	0.011		0.035	0.015	0.032
		(0.025)	(0.029)	(0.031)		(0.058)	(0.060)	(0.056)
($t-2$)			0.021	0.005			0.041	0.024
			(0.030)	(0.030)			(0.057)	(0.064)
($t-3$)				0.019				0.031
				(0.027)				(0.068)
($t-4$)				−0.062				0.028
				(0.033)				(0.058)
($t-5$)				0.022				−0.043
				(0.026)				(0.070)
Coverage of both sides attacking day...								
(t)	0.061***	0.035	0.035	0.032	0.029	−0.010	−0.013	−0.023
	(0.015)	(0.020)	(0.021)	(0.021)	(0.031)	(0.044)	(0.046)	(0.048)
($t-1$)		0.032*	0.017	0.007		0.039	0.019	0.011
		(0.016)	(0.020)	(0.019)		(0.047)	(0.063)	(0.062)
($t-2$)			0.025	0.002			0.019	−0.003
			(0.020)	(0.023)			(0.059)	(0.080)
($t-3$)				0.001				0.049
				(0.022)				(0.062)
($t-4$)				0.029				−0.043
				(0.023)				(0.060)
($t-5$)				0.020				0.007
				(0.023)				(0.046)
Coverage of Palestinian attacks day...								
(t)	0.052	0.053	0.047	0.054	0.158*	0.127	0.129	0.154*
	(0.031)	(0.034)	(0.035)	(0.037)	(0.066)	(0.072)	(0.072)	(0.074)
($t-1$)		−0.021	−0.023	−0.028		0.098	0.081	0.043
		(0.028)	(0.029)	(0.031)		(0.063)	(0.068)	(0.068)
($t-2$)			−0.017	−0.027			0.015	0.016
			(0.033)	(0.035)			(0.073)	(0.073)
($t-3$)				−0.005				0.017
				(0.030)				(0.073)
($t-4$)				0.018				0.032
				(0.033)				(0.076)
($t-5$)				0.056				0.071
				(0.033)				(0.067)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5700	5633	5566	5365	5700	5633	5566	5365
Mean dependent var.	2.370	2.369	2.366	2.363	0.449	0.449	0.447	0.440
SD of dependent var.	1.843	1.843	1.843	1.839	0.729	0.729	0.728	0.718
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.033	0.033	0.033	0.034	0.050	0.050	0.051	0.052
F-test Israeli attacks	0.001	0.039	0.136	0.288	0.193	0.416	0.564	0.809
F-test both sides attacking	0.000	0.000	0.000	0.002	0.342	0.650	0.875	0.946
F-test Palestinian attacks	0.099	0.307	0.511	0.404	0.016	0.003	0.023	0.090

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) – (4)) and Muslims (columns (5) – (8)). In columns (1) and (5), the independent variables are our measures of the length of conflict-related news in the United States. at day t. Subsequent columns gradually adds one, two and five lags of the independent variables. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: The effect of conflict news on placebo hate crime categories

	(1) Anti- Black	(2) Anti- Hispanic	(3) Anti- Black	(4) Anti- Hispanic
Length of conflict news, same day and previous day, covering...				
Israeli attacks	−0.000	0.004		
	(0.010)	(0.019)		
Both sides attacking	0.003	0.001		
	(0.005)	(0.010)		
Palestinian attacks	0.007	0.037		
	(0.012)	(0.024)		
Top 1% conflict news, same day and previous day, covering ...				
Israeli attacks			0.049	−0.054
			(0.054)	(0.117)
Both sides attacking			0.035	−0.047
			(0.054)	(0.112)
Palestinian attacks			0.010	0.053
			(0.055)	(0.112)
Bottom 99% conflict news, same day and previous day, covering ...				
Israeli attacks			0.002	0.041
			(0.023)	(0.058)
Both sides attacking			−0.007	−0.012
			(0.022)	(0.049)
Palestinian attacks			−0.009	0.079
			(0.024)	(0.060)
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure (t and t+1)	Yes	Yes	Yes	Yes
Observations	5633	5633	5633	5633
Mean dependent var.	6.364	1.249	6.364	1.249
SD of dependent var.	3.001	1.219	3.001	1.219
Model	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.057	0.032	0.057	0.032

Note: The dependent variables are the total number of hate crimes towards Blacks (columns (1) and (3)) and Hispanics (columns (2) and (4)). The dependent variables are the total number of hate crimes towards Jews (columns (1) and (3)) and Muslims (columns (2) and (4)). The independent variables are our measures of the length of conflict-related news aggregated for day t and $t - 1$ and two mutually exclusive dummy variables indicating days with less or top percentile news reporting within each type of reporting. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: Nonlinear effects of conflict news on hate crimes

	(1) Anti-Jewish	(2) Anti-Islamic
Coverage of Israeli attacks (t and $t-1$)		
>0 to 0.62 minutes	−0.056	−0.034
(percentiles: [92,95), 151 dates)	(0.058)	(0.154)
0.63 to 2.91 minutes	−0.007	0.086
(percentiles: [95,99), 219 dates)	(0.047)	(0.122)
2.92 to 13.6 minutes	0.234*	0.193
(percentiles: [99,100], 56 dates)	(0.097)	(0.155)
Coverage of both sides attacking (t and $t-1$)		
>0 to 0.77 minutes	0.091	0.039
(percentiles: [91,95), 179 dates)	(0.053)	(0.116)
0.78 to 4.22 minutes	0.096	0.147
(percentiles: [95,99), 223 dates)	(0.052)	(0.112)
4.23 to 17.2 minutes	0.300***	0.126
(percentiles: [99,100], 56 dates)	(0.089)	(0.216)
Coverage of Palestinian attacks (t and $t-1$)		
>0 to 0.11 minutes	−0.058	−0.068
(percentiles: [94,95), 42 dates)	(0.107)	(0.339)
0.16 to 2.27 minutes	0.007	0.155
(percentiles: [95,99), 213 dates)	(0.052)	(0.115)
2.33 to 8.5 minutes	0.092	0.377*
(percentiles: [99,100], 56 dates)	(0.082)	(0.156)
FEs (year, month, day of week)	Yes	Yes
Holidays and events	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes
Observations	5633	5633
Mean dependent var.	2.369	0.449
SD of dependent var.	1.843	0.729
Model	ML NB	ML NB
(Pseudo) R-squared	0.033	0.050
F-test Israeli attacks (p-value)	0.070	0.584
F-test both sides attacking (p-value)	0.001	0.599
F-test Palestinian attacks (p-value)	0.659	0.070

Note: The dependent variables are the total number of hate crimes towards Jews (column (1)) and Muslims (column (2)). The independent variables are our measures of the length of conflict-related news aggregated for day t and $t-1$ and categorized by mutually exclusive percentile dummy variables. The first variable indicates conflict news greater than 0 up to the 95th percentile, the second from the 95th percentile to the 99th percentile, and the last conflict news in the top percentile. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: Sensitivity checks: Introducing controls

Panel A: Conflict fatalities

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Jewish	(6) Anti-Jewish	(7) Anti-Islamic	(8) Anti-Islamic	(9) Anti-Islamic	(10) Anti-Islamic	(11) Anti-Islamic	(12) Anti-Islamic
Top 1% Israeli attacks (t and $t-1$)	0.348^{***}	0.348^{***}	0.347^{***}	0.351^{***}	0.321^{***}	0.322^{***}	0.265	0.279	0.285	0.269	0.257	0.272
(> 40 victims, 57 dates)	(0.091)	(0.092)	(0.093)	(0.093)	(0.087)	(0.087)	(0.213)	(0.216)	(0.211)	(0.209)	(0.198)	(0.198)
Top 1% Palestinian attacks (t and $t-1$)	0.071	0.056	0.057	0.056	0.045	0.045	0.434^{**}	0.438^{**}	0.442^{**}	0.440^{**}	0.411^{**}	0.413^{**}
(> 10 victims, 46 dates)	(0.079)	(0.080)	(0.080)	(0.080)	(0.079)	(0.079)	(0.153)	(0.157)	(0.156)	(0.157)	(0.155)	(0.155)
Smaller attacks from either side	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	-	Yes	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	Yes	Yes
Political events	-	-	Yes	Yes	Yes	Yes	-	-	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	-	-	-	Yes	Yes	Yes	-	-	-	Yes	Yes	Yes
2 lags dep. var	-	-	-	-	Yes	Yes	-	-	-	-	Yes	Yes
US targeted terrorist attack	-	-	-	-	-	Yes	-	-	-	-	-	Yes
Observations	5767	5767	5767	5765	5761	5761	5767	5767	5767	5765	5761	5761
Mean dependent var.	2.367	2.367	2.367	2.368	2.365	2.365	0.452	0.452	0.452	0.452	0.451	0.451
SD of dependent var.	1.845	1.845	1.845	1.845	1.843	1.843	0.733	0.733	0.733	0.732	0.732	0.732
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
(Pseudo) R-squared	0.027	0.031	0.032	0.032	0.033	0.033	0.044	0.048	0.049	0.051	0.053	0.054

Panel B: Conflict news

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Jewish	(6) Anti-Jewish	(7) Anti-Islamic	(8) Anti-Islamic	(9) Anti-Islamic	(10) Anti-Islamic	(11) Anti-Islamic	(12) Anti-Islamic
Top 1% Israeli Violence (t and $t-1$)	0.231^{*}	0.227^{*}	0.231^{*}	0.233^{*}	0.211^{*}	0.211^{*}	0.216	0.220	0.206	0.196	0.177	0.183
	(0.097)	(0.098)	(0.098)	(0.098)	(0.093)	(0.093)	(0.150)	(0.152)	(0.151)	(0.155)	(0.153)	(0.153)
Top 1% Both Violence (t and $t-1$)	0.308^{***}	0.316^{***}	0.316^{***}	0.309^{***}	0.269^{**}	0.269^{**}	0.108	0.133	0.137	0.139	0.100	0.105
	(0.091)	(0.091)	(0.091)	(0.091)	(0.086)	(0.086)	(0.216)	(0.213)	(0.210)	(0.212)	(0.208)	(0.209)
Top 1% Palestinian Violence (t and $t-1$)	0.080	0.090	0.092	0.089	0.080	0.080	0.380^{*}	0.378^{*}	0.373^{*}	0.381^{*}	0.388^{**}	0.386^{**}
	(0.084)	(0.083)	(0.083)	(0.083)	(0.081)	(0.081)	(0.155)	(0.154)	(0.153)	(0.156)	(0.150)	(0.150)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	-	Yes	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	Yes	Yes
Political events	-	-	Yes	Yes	Yes	Yes	-	-	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	-	-	-	Yes	Yes	Yes	-	-	-	Yes	Yes	Yes
2 lags dep. var	-	-	-	-	Yes	Yes	-	-	-	-	Yes	Yes
US targeted terrorist attack	-	-	-	-	-	Yes	-	-	-	-	-	Yes
Observations	5635	5635	5635	5633	5631	5631	5635	5635	5635	5633	5631	5631
Mean dependent var.	2.369	2.369	2.369	2.369	2.368	2.368	0.449	0.449	0.449	0.449	0.449	0.449
SD of dependent var.	1.843	1.843	1.843	1.843	1.843	1.843	0.729	0.729	0.729	0.729	0.729	0.729
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
(Pseudo) R-squared	0.021	0.032	0.032	0.033	0.034	0.034	0.038	0.047	0.048	0.050	0.053	0.053

Note: The dependent variables are the total number of hate crimes toward Jews (columns (1) – (5)) and Muslims (columns (6) – (10)). The independent variables in Panel A are days with top percentile attacks from each side on day t and $t-1$, and in Panel B days with top percentile news reporting on day t or $t-1$, split by type of violence reported on. Controls are presented in Section 3. All models are estimated using a maximum-likelihood negative binomial model. Newey-West standard errors allowing for autocorrelation of up to seven lags in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A14: Sensitivity checks: Dropping conflict periods

Panel A: Conflict fatalities

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Jewish	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic	(9) Anti-Islamic	(10) Anti-Islamic
Excluded period	None	Second Intifada	Cast Lead	Pillar of Defense	Protective Edge	None	Second Intifada	Cast Lead	Pillar of Defense	Protective Edge
Top 1% Israeli attacks (t and $t-1$)	0.351***	0.357***	0.458***	0.333**	0.227*	0.269	0.075	0.353	0.192	0.228
(> 40 victims, 57 dates)	(0.093)	(0.107)	(0.092)	(0.101)	(0.109)	(0.209)	(0.238)	(0.227)	(0.232)	(0.298)
Top 1% Palestinian attacks (t and $t-1$)	0.056	0.226	0.048	0.058	0.044	0.440**	0.884*	0.433**	0.442**	0.403*
(> 10 victims, 46 dates)	(0.080)	(0.277)	(0.080)	(0.080)	(0.082)	(0.157)	(0.361)	(0.156)	(0.157)	(0.167)
Smaller attacks from either side	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs, holidays, events, news pressure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5765	4367	5742	5757	5715	5765	4367	5742	5757	5715
Mean dependent var.	2.368	2.244	2.367	2.367	2.366	0.452	0.464	0.453	0.451	0.451
SD of dependent var.	1.845	1.756	1.844	1.844	1.848	0.732	0.745	0.733	0.732	0.733
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
Share vics. excluded fr. PA	0.000	0.756	0.008	0.005	0.062	0.000	0.756	0.008	0.005	0.062
Share vics. excluded fr. IA	0.000	0.318	0.155	0.019	0.246	0.000	0.318	0.155	0.019	0.246
(Pseudo) R-squared	0.032	0.030	0.032	0.032	0.033	0.051	0.052	0.051	0.051	0.051

Panel B: Conflict news

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Jewish	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic	(9) Anti-Islamic	(10) Anti-Islamic
Excluded period	None	Second Intifada	Cast Lead	Pillar of Defense	Protective Edge	None	Second Intifada	Cast Lead	Pillar of Defense	Protective Edge
Top 1% Israeli violence (t and $t-1$)	0.233*	0.199	0.316***	0.229*	0.177	0.196	-0.165	0.250	0.220	0.207
	(0.098)	(0.213)	(0.091)	(0.098)	(0.095)	(0.155)	(0.282)	(0.163)	(0.153)	(0.164)
Top 1% Both violence (t and $t-1$)	0.309***	0.078	0.336***	0.328***	0.317**	0.139	0.521*	0.085	-0.022	0.108
	(0.091)	(0.113)	(0.094)	(0.097)	(0.097)	(0.212)	(0.253)	(0.231)	(0.221)	(0.244)
Top 1% Palestinian violence (t and $t-1$)	0.089	0.432	0.086	0.086	0.046	0.381*	0.025	0.393*	0.406**	0.379*
	(0.083)	(0.263)	(0.083)	(0.083)	(0.076)	(0.156)	(0.502)	(0.156)	(0.154)	(0.165)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs, holidays, events, news pressure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5633	4251	5610	5627	5583	5633	4251	5610	5627	5583
Mean dependent var.	2.369	2.247	2.368	2.369	2.367	0.449	0.460	0.450	0.448	0.448
SD of dependent var.	1.843	1.756	1.842	1.844	1.846	0.729	0.741	0.729	0.728	0.729
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
Share conflict news excl.	0.000	0.621	0.054	0.024	0.075	0.000	0.621	0.054	0.024	0.075
(Pseudo) R-squared	0.033	0.031	0.033	0.033	0.034	0.050	0.051	0.050	0.050	0.050

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) – (5)) and Muslims (columns (6) – (10)). The independent variables in Panel A are days with top percentile attacks from each side day t and $t-1$, and in Panel B days with top percentile news reporting day t and $t-1$, split by type of violence reported on. Columns (1) and (5) includes the whole sample period from 2000 to 2016, while subsequent columns exclude one conflict period at the time. The definitions of these conflict periods are further explained in Section 3. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A15: Sensitivity checks: Violent conflict news and dropping conflict periods

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Jewish	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic	(9) Anti-Islamic	(10) Anti-Islamic
Excluded period	None	Second Intifada	Cast Lead	Pillar of Defense	Protective Edge	None	Second Intifada	Cast Lead	Pillar of Defense	Protective Edge
Top 1% violent conflict news (t and $t-1$)	0.421***	0.356*	0.431***	0.430***	0.390***	0.436*	0.453	0.433*	0.327	0.456*
	(0.081)	(0.163)	(0.083)	(0.090)	(0.082)	(0.177)	(0.276)	(0.190)	(0.188)	(0.187)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs, holidays, events, news pressure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5700	4309	5677	5693	5650	5700	4309	5677	5693	5650
Mean dependent var.	2.370	2.247	2.369	2.369	2.368	0.449	0.460	0.450	0.448	0.448
SD of dependent var.	1.843	1.754	1.842	1.843	1.846	0.729	0.741	0.730	0.729	0.730
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
Share conflict news excl.	0.000	0.621	0.054	0.024	0.075	0.000	0.621	0.054	0.024	0.075
(Pseudo) R-squared	0.032	0.030	0.033	0.032	0.034	0.050	0.051	0.050	0.050	0.050

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) – (5)) and Muslims (columns (6) –10). The independent variable is days with top percentile news reporting day t and $t-1$. Columns (1) and (5) includes the whole sample period from 2000 to 2016, while subsequent columns excludes one conflict period at the time. The definition of these conflict periods are further explained in Section 3. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A16: Sensitivity checks: Dropping states

Panel A: Conflict fatalities

	(1) Anti-Jewish (no CA)	(2) Anti-Jewish (no NJ)	(3) Anti-Jewish (no NY)	(4) Anti-Muslim (no CA)	(5) Anti-Muslim (no NJ)	(6) Anti-Muslim (no NY)
Top 1% Israeli attacks (t and $t-1$)	0.304**	0.379***	0.348***	0.292	0.220	0.069
(> 40 victims, 57 dates)	(0.098)	(0.096)	(0.096)	(0.218)	(0.218)	(0.232)
Top 1% Palestinian attacks (t and $t-1$)	0.040	0.092	0.099	0.517**	0.464**	0.435**
(> 10 victims, 46 dates)	(0.085)	(0.089)	(0.090)	(0.160)	(0.160)	(0.159)
Smaller attacks from either side	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5765	5765	5765	5765	5765	5765
Mean dependent var.	2.008	1.873	1.755	0.393	0.419	0.405
SD of dependent var.	1.685	1.579	1.557	0.672	0.701	0.687
Share of hate crimes excluded	0.152	0.209	0.259	0.130	0.072	0.104
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
F-test Independent variable(s)	0.012	0.000	0.002	0.004	0.017	0.057
(Pseudo) R-squared	0.029	0.025	0.041	0.049	0.054	0.049

Panel B: Conflict news

	(1) Anti-Jewish (no CA)	(2) Anti-Jewish (no NJ)	(3) Anti-Jewish (no NY)	(4) Anti-Muslim (no CA)	(5) Anti-Muslim (no NJ)	(6) Anti-Muslim (no NY)
Top 1% Israeli violence (t and $t-1$)	0.161	0.316**	0.146	0.051	0.173	0.270
	(0.102)	(0.109)	(0.107)	(0.174)	(0.191)	(0.155)
Top 1% both violence (t and $t-1$)	0.221*	0.355***	0.234*	0.128	0.166	-0.070
	(0.102)	(0.094)	(0.113)	(0.239)	(0.232)	(0.218)
Top 1% Palestinian violence (t and $t-1$)	0.117	0.087	0.103	0.382*	0.441**	0.428**
	(0.088)	(0.094)	(0.097)	(0.160)	(0.167)	(0.161)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5633	5633	5633	5633	5633	5633
Mean dependent var.	2.009	1.870	1.760	0.391	0.417	0.402
SD of dependent var.	1.684	1.576	1.557	0.669	0.698	0.683
Share of hate crimes excluded	0.152	0.209	0.259	0.130	0.072	0.104
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
F-test Independent variable(s)	0.000	0.000	0.000	0.000	0.000	0.000
(Pseudo) R-squared	0.030	0.026	0.041	0.048	0.054	0.048

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) – (3)) and Muslims (columns (4) – (6)). The independent variables in Panel A are days with top percentile attacks from each side day t and $t-1$, and in Panel B days with top percentile news reporting day t and $t-1$, split by type of violence reported on. Columns (1) and (4) exclude hate crimes in California, columns (2) and (5) exclude hate crimes in the state of New Jersey, while columns (3) and (6) exclude hate crimes in the state of New York. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A17: Sensitivity checks: Model specification

Panel A: Conflict fatalities

	(1) Anti-Jewish	(2) Anti-Islamic	(3) Ln(Anti-Jewish+1)	(4) Ln(Anti-Islamic+1)	(5) Anti-Jewish	(6) Anti-Islamic	(7) Any Anti-Jewish	(8) Any Anti-Islamic
Top 1% Israeli attacks (t and $t-1$)	0.351***	0.269	0.256**	0.082	0.866***	0.139	0.414	0.249
(> 40 victims, 57 dates)	(0.093)	(0.209)	(0.081)	(0.067)	(0.250)	(0.115)	(0.286)	(0.221)
Top 1% Palestinian attacks (t and $t-1$)	0.056	0.440**	0.053	0.141*	0.156	0.260*	0.210	0.362*
(> 10 victims, 46 dates)	(0.080)	(0.157)	(0.067)	(0.061)	(0.227)	(0.112)	(0.286)	(0.172)
Smaller attacks from either side	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5765	5765	5765	5765	5765	5765	5669	5765
Mean dependent var.	2.368	0.452	1.062	0.278	2.368	0.452	0.862	0.341
SD of dependent var.	1.845	0.732	0.572	0.408	1.845	0.732	0.345	0.474
Model	ML NB	ML NB	OLS	OLS	OLS	OLS	Probit	Probit
Pseudo R-squared	0.032	0.051	0.109	0.089	0.112	0.095	0.061	0.056

Panel B: Conflict news

	(1) Anti-Jewish	(2) Anti-Islamic	(3) Ln(Anti-Jewish+1)	(4) Ln(Anti-Islamic+1)	(5) Anti-Jewish	(6) Anti-Islamic	(7) Any Anti-Jewish	(8) Any Anti-Islamic
Top 1% Israeli violence (t and $t-1$)	0.233*	0.196	0.174	0.066	0.724*	0.107	0.125	0.223
	(0.098)	(0.155)	(0.095)	(0.048)	(0.327)	(0.087)	(0.300)	(0.146)
Top 1% both violence (t and $t-1$)	0.309***	0.139	0.234**	0.035	1.085**	0.082	0.376	0.057
	(0.091)	(0.212)	(0.077)	(0.060)	(0.386)	(0.107)	(0.304)	(0.198)
Top 1% Palestinian violence (t and $t-1$)	0.089	0.381*	0.078	0.114*	0.231	0.217*	−0.019	0.283
	(0.083)	(0.156)	(0.074)	(0.056)	(0.237)	(0.105)	(0.239)	(0.164)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5633	5633	5633	5633	5633	5633	5539	5633
Mean dependent var.	2.369	0.449	1.063	0.276	2.369	0.449	0.862	0.339
SD of dependent var.	1.843	0.729	0.572	0.407	1.843	0.729	0.345	0.474
Model	ML NB	ML NB	OLS	OLS	OLS	OLS	Probit	Probit
Pseudo R-squared	0.033	0.050	0.112	0.087	0.116	0.093	0.062	0.055

Note: The independent variables in Panel A are days with top percentile attacks from each side day t and $t-1$, and in Panel B days with top percentile news reporting day t and $t-1$, split by type of violence reported on. The dependent variables are either the total number of hate crimes towards Jews or Muslims (columns (1) – (2), (5) – (6)), the analogous variables logged (columns (3) – (4)) or collapsed into a dummy indicating the occurrence of at least one hate crime (columns (7) – (8)). Columns (1) and (2) are estimated using a maximum-likehood negative binomial model, columns (3) – (6) uses OLS, and columns (7) – (8) uses a Probit regression. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. Newey-West standard errors allowing for autocorrelation of up to seven lags are presented in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A18: Sensitivity checks: Panel or lag structure

	Weekly data				Daily data			
	(1) Anti-Jewish	(2) Anti-Islamic	(3) Anti-Jewish	(4) Anti-Islamic	(5) Anti-Jewish	(6) Anti-Islamic	(7) Anti-Jewish	(8) Anti-Islamic
Victims week t from...								
Israeli attacks	0.001**	−0.000						
	(0.000)	(0.000)						
Palestinian attacks	0.003	0.026**						
	(0.003)	(0.010)						
Conflict news week t covering...								
Israeli attacks			0.010	0.030				
			(0.010)	(0.017)				
Both sides attacking			0.012***	0.002				
			(0.004)	(0.007)				
Palestinian attacks			0.011	0.052*				
			(0.008)	(0.021)				
Victims day t to $t-2$ from...								
Israeli attacks					0.001**	0.001		
					(0.000)	(0.001)		
Palestinian attacks					0.003	0.013		
					(0.004)	(0.008)		
Conflict news day t to $t-2$ covering...								
Israeli attacks							0.027*	0.032
							(0.012)	(0.023)
Both sides attacking							0.026***	0.009
							(0.005)	(0.013)
Palestinian attacks							0.001	0.077**
							(0.014)	(0.027)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FEs	-	-	-	-	Yes	Yes	Yes	Yes
Holidays and events	-	-	-	-	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	-	-	-	-	Yes	Yes	Yes	Yes
Observations	824	824	824	824	5761	5761	5566	5566
Mean dependent var.	16.568	3.163	16.568	3.163	2.365	0.451	2.366	0.447
SD of dependent var.	6.561	2.629	6.561	2.629	1.843	0.732	1.843	0.728
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.058	0.083			0.031	0.050		
p-value Isr. attack $\beta^{Jew} = \beta^{Isl}$	0.023		0.197		0.738		0.814	
p-value both attacking $\beta^{Jew} = \beta^{Isl}$			0.224				0.154	
p-value Pal. attack $\beta^{Jew} = \beta^{Isl}$	0.033		0.224		0.264		0.154	

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1), (3), (5) and (7)) and Muslims (columns (2), (4), (6) and (8)). The independent variables are the number of victims from Israeli and Palestinian attacks (columns (1), (2), (5) and (6)), or the length of conflict news reporting (columns (3), (4), (7), and (8)). Columns (1) – (4) collapse the data to weekly level and regress the independent variables week t on the same week aggregates of hate crimes, controlling for year and calendar month fixed effects. Columns (5) – (8) use daily level data, but use as independent variables the aggregate of the past three days. Models in the daily data set in columns (5) – (8) control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. The last three rows present the p-values of a test for equality between the effects of Israeli or Palestinian attacks, or the analogous news variables, on anti-Jewish and anti-Islamic hate crimes estimated using seemingly unrelated regressions. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags in the daily data set, and four weeks in the weekly data set.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A19: Sensitivity checks: Agency robustness

	(1) Anti-Jewish	(2) Anti-Muslim	(3) Anti-Jewish	(4) Anti-Muslim
Top 1% victims, same day or previous day, from...				
Israeli attacks	0.431^{***}	0.299		
	(0.096)	(0.213)		
Palestinian attacks	-0.017	0.460^{**}		
	(0.090)	(0.177)		
Top 1% conflict news, same day or previous day, covering...				
Israeli attacks			0.252^{*}	0.229
			(0.103)	(0.159)
Both sides attacking			0.273^{**}	0.132
			(0.098)	(0.236)
Palestinian attacks			0.047	0.366^{*}
			(0.101)	(0.179)
Smaller attacks from either side	Yes	Yes	-	-
Bottom 99% reporting	-	-	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes
Observations	5765	5765	5633	5633
Mean dependent var.	2.184	0.420	2.186	0.418
SD of dependent var.	1.830	0.713	1.828	0.709
Share of hate crimes included	0.923	0.931	0.923	0.931
Model	ML NB	ML NB	ML NB	ML NB
(Pseudo) R-squared	0.025	0.053	0.026	0.053

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) and (3)) and Muslims (columns (2) and (4)). The independent variables are top percentile Israeli and Palestinian attacks (columns (1) and (2)) and top percentile conflict news reporting (columns (3) and (4)). The sample is restricted to agencies that, once they started partaking in the Uniform Crime Program, remained in the program for the sample period. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A20: Sensitivity checks: Main results and future larger attacks

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Islamic	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic
Top 1% Israeli attacks day...								
($t+3$)				0.009				−0.106
				(0.139)				(0.237)
($t+2$)			0.101	0.096			−0.288	−0.295
			(0.091)	(0.104)			(0.340)	(0.340)
($t+1$)		0.087	0.040	0.047		−0.085	−0.028	−0.048
		(0.099)	(0.111)	(0.115)		(0.240)	(0.238)	(0.255)
(t and $t-1$)	0.351***	0.290**	0.261**	0.259**	0.269	0.215	0.238	0.248
	(0.093)	(0.096)	(0.097)	(0.100)	(0.209)	(0.251)	(0.266)	(0.263)
Top 1% Palestinian attacks day...								
($t+3$)				−0.209*				0.225
				(0.106)				(0.173)
($t+2$)			0.160	0.158			0.072	0.031
			(0.090)	(0.090)			(0.198)	(0.205)
($t+1$)		0.071	0.057	0.058		0.338	0.286	0.282
		(0.129)	(0.125)	(0.124)		(0.210)	(0.217)	(0.218)
(t and $t-1$)	0.056	0.048	0.051	0.048	0.440**	0.399*	0.368*	0.360*
	(0.080)	(0.078)	(0.078)	(0.080)	(0.157)	(0.157)	(0.159)	(0.165)
Smaller attacks from either side	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5765	5765	5763	5761	5765	5765	5763	5761
Mean dependent var.	2.368	2.368	2.368	2.368	0.452	0.452	0.451	0.450
SD of dependent var.	1.845	1.845	1.845	1.845	0.732	0.732	0.731	0.731
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
F-test Isr. leads (p-value)		0.381	0.371	0.554		0.722	0.652	0.696
F-test Pal. leads (p-value)		0.580	0.195	0.077		0.107	0.364	0.275
(Pseudo) R-squared	0.032	0.032	0.032	0.032	0.051	0.052	0.053	0.053

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) – (4)) and Muslims (columns (5) – (8)). The independent variables are days with top percentile attacks from each side day t and $t-1$, controlling for top percentile attacks day $t+1$ (the day after) up to t+3. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A21: Sensitivity checks: Main results and future extensive coverage of attacks

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Jewish	(4) Anti-Jewish	(5) Anti-Islamic	(6) Anti-Islamic	(7) Anti-Islamic	(8) Anti-Islamic
Top 1% coverage of Israeli attacks day...								
(t+3)				0.050				−0.008
				(0.094)				(0.259)
(t+2)			0.077	0.056			−0.247	−0.260
			(0.107)	(0.110)			(0.239)	(0.241)
($t+1$)		0.003	−0.023	−0.022		0.149	0.130	0.125
		(0.083)	(0.082)	(0.084)		(0.187)	(0.198)	(0.196)
($t+t-1$)	0.233*	0.234*	0.217*	0.208*	0.196	0.114	0.091	0.080
	(0.098)	(0.097)	(0.094)	(0.093)	(0.155)	(0.166)	(0.174)	(0.168)
Top 1% coverage of both attacking day...								
($t+3$)				0.079				−0.069
				(0.103)				(0.225)
($t+2$)			0.200	0.153			−0.056	−0.031
			(0.104)	(0.122)			(0.239)	(0.280)
($t+1$)		0.060	−0.032	−0.011		0.411	0.376	0.384
		(0.105)	(0.115)	(0.114)		(0.219)	(0.227)	(0.245)
($t+t-1$)	0.309***	0.295**	0.251*	0.221	0.139	−0.213	−0.091	−0.069
	(0.091)	(0.103)	(0.118)	(0.120)	(0.212)	(0.258)	(0.269)	(0.281)
Top 1% coverage of Palestinian attacks day...								
($t+3$)				−0.021				0.038
				(0.093)				(0.189)
($t+2$)			0.117	0.130			−0.044	−0.041
			(0.099)	(0.102)			(0.165)	(0.167)
($t+1$)		0.029	0.004	−0.006		−0.106	−0.152	−0.219
		(0.088)	(0.094)	(0.094)		(0.213)	(0.220)	(0.218)
($t+t-1$)	0.089	0.094	0.064	0.072	0.381*	0.339*	0.355*	0.296
	(0.083)	(0.085)	(0.086)	(0.085)	(0.156)	(0.166)	(0.165)	(0.168)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, day of week)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays and events	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News pressure (t and $t+1$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5633	5568	5501	5434	5633	5568	5501	5434
Mean dependent var.	2.369	2.359	2.356	2.359	0.449	0.446	0.445	0.444
SD of dependent var.	1.843	1.834	1.830	1.832	0.729	0.726	0.722	0.721
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
(Pseudo) R-squared	0.033	0.033	0.033	0.034	0.050	0.052	0.053	0.053
F-test Isr. attacks leads (p-value)		0.973	0.722	0.820		0.426	0.537	0.714
F-test Both attacks leads (p-value)		0.566	0.139	0.079		0.061	0.248	0.480
F-test Pal. attacks leads (p-value)		0.742	0.473	0.436		0.619	0.703	0.537

Note: The dependent variables are the total number of hate crimes towards Jews (columns (1) − (4)) and Muslims (columns (5) − (8)). The independent variables are days with top percentile news reporting day t and $t-1$, split by type of violence reported on, controlling for the analogous variables for top percentile conflict reporting day $t+1$ (the day after) up to $t+3$. All models control for year, calendar month and day of the week fixed effects, as well as a set of controls for holidays, events, and news pressure, described in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for autocorrelation of up to seven lags presented in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$