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Echoes of Violent Conflict: The Effect of the Israeli-Palestinian Conflict on Hate Crimes in the U.S.

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Abstract

Do social identity ties facilitate the spread of violent conflict? We assess whether the Israeli-Palestinian conflict causes hate crime towards Jews and Muslims in the U.S using daily data between 2000-2016. We measure the timing, intensity and instigator in the conflict using the number of conflict fatalities and U.S. mass media coverage of the conflict. Analyses using both conflict measures find that conflict events trigger hate crimes in the following 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. Moreover, the lack of an effect of non-violent conflict reporting suggests that hate crimes are not triggered by the salience of the Israeli-Palestinian conflict in itself. Our findings suggest 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, 27 countries have experienced violent ethnic conflicts with more than 25 battle-related deaths per year (Vogt et al., 2015). At least 500 million people have ethnic ties to these conflicts and reside in countries not involved in the conflict.[1] Existing research shows that conflicts are more likely to spill over when there are ethnic ties between the regions or countries (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 if social identity ties facilitate the spread of violent conflict. Research on conflict spillover primarily focuses 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 (Lake and Rothchild, 1998; Kuran, 1998) and several studies conclude 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 mechanisms 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 the spread of violence, it is still unclear exactly why. Except for the spurring of animosity through social identities, ethnic violence might spread for instrumental reasons (Weidmann, 2015). For example, political success of co-ethnics abroad might shift beliefs about the chances for political success at home, increasing the risk 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 conflict. By lifting

[1]These estimates are based on calculations using the Ethnic Power Relations Dataset (Wucherpfennig et al., 2012) and data from the Joshua Project (joshuaproject.net). First, using the Ethnic Power Relations Dataset, we identify all conflicts that are currently ongoing or ended after 2010. We then map the ethnic groups involved in the conflict 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 which belong to the ethnic group involved in the conflict, that reside in another country 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.

[3]For instance, the existence of regionally active violent underground actors and markets for violence, which has been shown to facilitate the spread of violence (Silve and Verdier, 2018), might be correlated with cross-border ethnic ties.

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 inter-group 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 Turkish and Kurdish diaspora in response to the Turkisk military operation into northeast Syria in 2019. In France, Turkisk, Azeri and Armenian diaspora clashed following the escalating conflict in Nagorno-Karabach in 2020.[4] In our setting, the Israeli-Palestinian conflict has been reported to trigger hate crimes and animosity primarily against Jews in both the U.S. and Europe.[5]. This type of mechanism is also supported by studies on how anti-Islamic hate crimes are triggered by jihadist terrorist attacks targeting U.S. or Western European civilians, such as the 9/11 attacks in the U.S. or the 7/7 attacks in London (Disha, Cavendish and King, 2011; King and Sutton, 2013; Hanes and Machin, 2014; Ivandic et al., 2019). Terrorist attacks have furthermore been shown to induce ethnic discrimination within the criminal justice system (Shayo and Zussman, 2011), even against other ethnic groups than those of the terrorists (McConnell and Rasul, 2018). Yet, these studies on terrorist attacks focus on the effect on hate crimes or discrimination in the country and by the populace under attack, and are mute on how identity ties may facilitate the spread of animosity among individuals who are neither involved 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 longstanding and divisive violent conflicts fought along ethnic and religious lines in the postwar era: the Israeli-Palestinian conflict. Using daily data between 2000 and 2016, we examine if the Israeli-Palestinian conflict causes hate crime towards Jews and Muslims in the U.S. 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 religiously motivated hate crimes in the U.S., accounting for approximately 12% and 4% of the estimated 250,000 annual hate crimes (BJS, 2013). The geographic and contextual distance between the

[4]See "Brawls between Kurds and Turks injure several across Germany", *Deutsch Welle*, 17-19-2019, Accessed 04-08-2021, and "Video shows Turkish and Azeri nationals 'looking for Armenians' in France", *The Independent*, 29-10-2020, Accessed 04-08-2021.

[5]For examples in the U.S. see e.g. "2014 Audit of Anti-Semitic Incidents", *Anti-Defamation League*, Accessed 24-05-2021. For Europe, see e.g. FRA (2018) and Enstad (2017)

[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 offenders bias against a race, religion, disability, sexual orientation, or ethnicity/national origin."*

Middle East and the U.S. and our choice to estimate the effect of the conflict on hate crime within a time window of a few days ameliorates several of the endogeneity problems from previous studies. This makes it plausible that we isolate the effect of animosity transmitted through the identity 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 U.S. 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 if the identity of the attacker matters for which group is victimized in the U.S. Compared to the fatalities data, the news data is better at capturing the degree to which U.S. audiences are exposed to events from the conflict and how the events are framed. This is important since previous research shows that the Israeli Defence Forces appear to time attacks to minimize U.S. 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 non-fatal attacks and provide us with a measure of non-violent 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 primarily driven by days with large attacks and days with extensive media reporting. Fatalities from Israeli attacks today and yesterday in the top percentile (40 fatal victims or more) increases the expected number of anti-Jewish hate crimes by 35%. The analogous Palestinian attack (10 fatal victims or more) increases the expected number of anti-Islamic hate crimes by 44%. Similarly, news reporting on Israeli violence today and yesterday in the top percentile (3 minutes or more) increases anti-Jewish hate crime by 23% and top percentile news reporting on Palestinian violence (2.3 minutes or more) increases anti-Islamic hate crime by 38%.

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 U.S. 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 U.S. that also affect the levels of hate crime. To alleviate such concerns, we control for religious and federal holidays, as well as major political events and U.S. news pressure. Overall, our results are largely unaffected by dropping various conflict periods, indicating quite homogeneous effects over time. In addition, using our news data, we show that news reporting on violence in the 2006 Israel-Lebanon War increased hate crimes against Jews and Muslims in the U.S., showing that our findings at least generalize to the broader Arab-Israeli conflict. We also find little evidence of violent spillover on ethnic groups that are not associated with the conflict actors (cf. McConnell and Rasul, 2018), 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 U.S. Finally, the results are robust to dropping individual states that dominate hate crime reporting and using alternative model specifications and lag structures.

Taken together, the findings indicate that perpetrators, in our setting, are driven by a retaliatory motive. First, the identity of the attacker matters for which group in the U.S. is subjected to hate crimes. Second, there is no effect of non-violent 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. One possible explanation for this pattern is that perpetrators identify with attack victims and that conflict violence generates a retaliatory motive towards 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. An alternative explanation, which is not mutually exclusive and cannot be ruled out, is that perpetrators do not have such ties, but primarily have strong out-group 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 U.S.

The findings from this study show how social identities facilitate the spread of violence and contribute to our understanding of how, when and where conflict can have violent 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 on their targeted communities, they are considered to be particularly serious compared to similar non-hate motivated offences. For example, Gould and Klor (2016) show that the increase of anti-Islamic hate crimes in the U.S. in the aftermath of 9-11 had large and lasting effects for the entire U.S. Muslim population, inducing a slow-down of the assimilation of American Muslims, strengthening their ethnic identity, and lowering female labor force participation. 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, but 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. Section 4 and 5 present the empirical strategy and results, respectively, while Section 6 concludes.

2 The Israeli-Palestinian Conflict and its Religious and Ethnic Dimension

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, that led to Israel occupying the Gaza Strip and the West Bank. Our analysis covers the period 2000-2016 and the subsequent section will describe 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 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 and 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 crime 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 U.S. trigger animosity and hate crimes directed at American Muslims. We hypothesize that a similar mechanism is at play in the Israeli-Palestinian conflict, despite the fact that 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 Jews, Muslims and Arabs in the U.S. are associated with actors in the conflict by potential hate crime perpetrators, 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 U.S. 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 (USCB, 2016).[7] A 2016 Gallup survey found that 2.1% of the U.S. population identify as Jewish and 0.8% identify as Muslim.[8]

[7] The Census Bureau defines ancestry as the ethnic origin, descent, roots, heritage, or place of birth of the person or of the persons ancestors. We include descendants of Algerian, Bahraini, Egyptian, Emirati, Iraqi, Jordanian, Kuwaiti, Lebanese, Libyan, Moroccan, Omani, Palestinian, Qatari, Saudi Arabian, Syrian, Tunisian, and Yemeni origin.

[8] "Five Key Findings on Religion", Gallup, 23 December, 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

Data on incidents of hate crime in the U.S. are obtained from the Uniform Crime Reports (UCR), which are compiled and supplied by the Federal Bureau of Investigation (FBI). Under the Hate Crime Statistics Act of 1990, all law enforcement agencies in the U.S. are asked to submit counts of hate crime incidents in their jurisdiction.[9] 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 percent of all agencies, covering 290 million people or 90 percent of the U.S. 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). Under-reporting of hate crimes, both on the part of police agencies and individuals, is a well-documented and persistent problem (e.g. BJS 2013 and King, Messner and Baller 2009). We ameliorate the selection problem by estimating the effect of the conflict on hate crimes by comparing the number of reported hate crimes within the span of a few days of an attack or event. Consequently, it is unlikely that any reporting bias across jurisdictions or over longer time periods pose a threat to establish causality. However, since we are using data on reported hate crimes, we cannot rule out that the treatment effects 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. This makes it the most common religiously motivated hate crime. Anti-Islamic hate crimes are the second most common religiously motivated hate crime, accounting for 2% of all hate crimes. Figure 1 shows the monthly number of reported anti-Jewish and anti-Islamic hate crimes between 2000-2016 in the US. The two types of hate crime converge during the period: anti-Jewish hate crime steadily decreases and anti-Islamic hate crime increases somewhat.[10] Two distinct spikes in hate crime are seen. Anti-Jewish hate crimes spike in October 2000, coinciding with the start of the Second Intifada[11]. Anti-

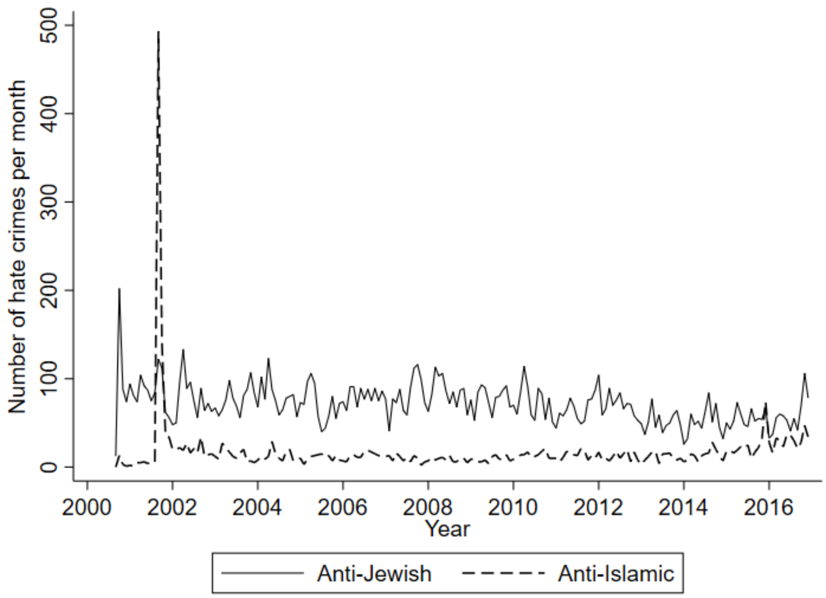
[9] If possible, the agencies should provide data on the nature of the offense, location, and characteristics of the offender and victim.

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

[11] This period of intense fighting commenced in September/October 2000 with a number of controversial events,

Islamic hate crime peaks 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 coincides with the Second Intifada, we omit the six months following the 9/11 attacks in our main analysis.

Figure 1: Number of Anti-Jewish and Anti-Islamic Hate Crimes in the USA 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 U.S. between 09-29-2000 – 12-31-2016. Note that this figure includes the 9/11 period, which we exclude in the other figures and tables which contain hate crime data.

Our data includes 13,652 accounts of anti-Jewish hate crime and 2,606 accounts of anti-Islamic hate crime. 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 and most anti-Islamic hate crime occurred in California, Michigan, and New York. The most common location for both anti-Jewish and anti-Islamic hate crime is at the residence of the victim. Both types of hate crimes are distributed uniformly across the month of the year and weekdays. Appendix Tables A1 and A2 show summary statistics for the type, location and seasonal variation of anti-Jewish and anti-Islamic hate crime in our sample.

including the visit of Ariel Sharon to the Temple Mount. The connection between the start of the Second Intifada and hate crimes in the U.S. were also identified by various U.S. news outlets in October 2001. See, for instance, "New Hostility in Mideast Echoes in a Brooklyn Neighborhood", New York Times, 10-05-2000, Accessed 09-04-2019.

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*.[12] Every fatal attack by the Israel Defense Forces (IDF) or Palestinian militants from 29 September 2000, the start of the Second Intifada, to the end of 2016, are included.

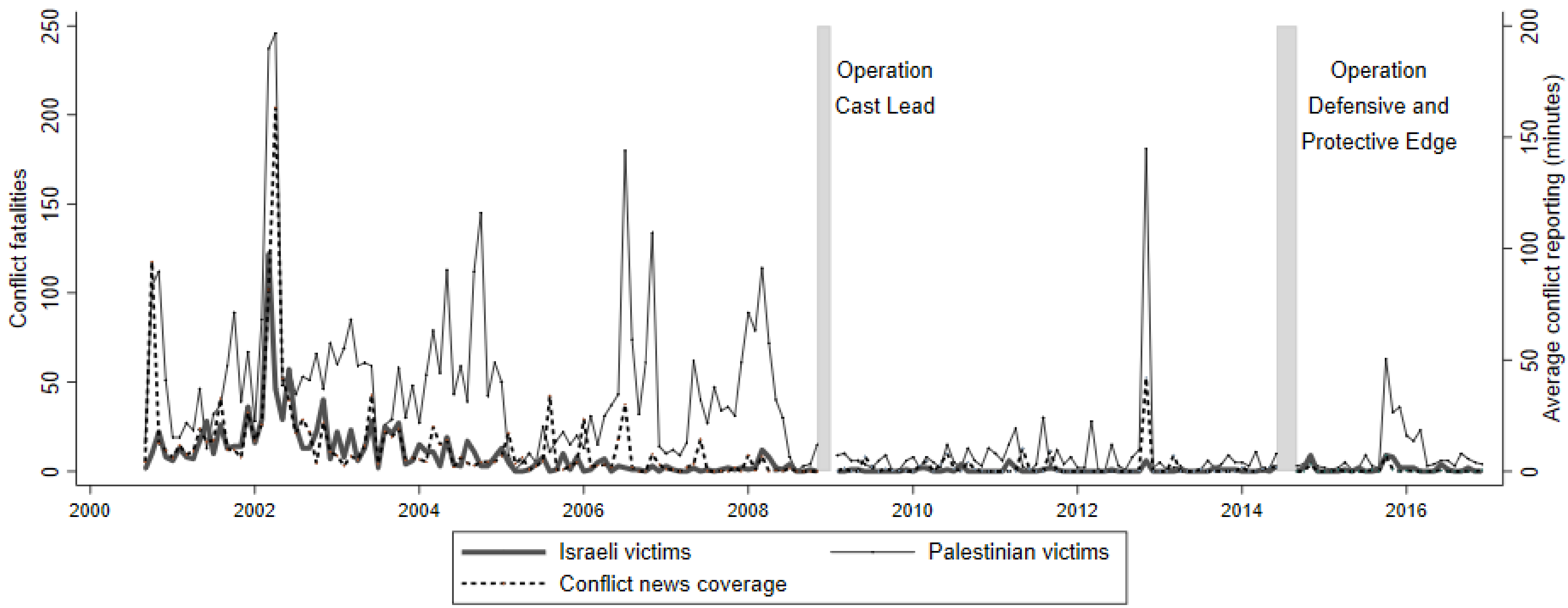
As can be seen in Figure 2, our sample period is characterized by periodically intense fighting between the Israeli Defence Forces and Palestinian militants. In September 2000, Palestinians initiated an uprising against the Israeli occupation, the Second Intifada, which lasted until 2005, claiming approximately 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 from 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 is characterized by long periods of 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 from 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 that had an attack, for each conflict period and the entire sample. The three aforementioned Israeli military operations were particularly intense, generating respectively 61, 22 and 46 fatalities per day on average. In contrast, the periods between Cast Lead and Pillar of Defense and after Protective Edge are characterized by less intense violence, with a daily incidence of fatalities of 13% and 21%, respectively, driven

[12] The B'Tselem data is commonly used in scholarship on the Israeli-Palestinian conflict. See, for instance, Jaeger and Paserman (2008) and 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 number of total conflict news coverage on ABC, CBS and NBC per month in the U.S. between 09-29-2000 – 12-31-2016 with the exception of two particularly intense conflict periods: Operation Cast Lead and Operation Defensive and 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.

mostly by Palestinian victims. The incidence of fatal attacks is generally high. 35% of the days in our sample had a fatal attack, averaging 1.7 victims. This is 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. 70% of days with a Palestinian fatal attack also have an Israeli attack. Conversely, 15% of days with a Israeli fatal attack also have a Palestinian attack.

Columns 5-8 in Appendix Table A1 present summary statistics of the total number of fatalities on each side and the distribution across weekdays and calendar months. There were a total of 1,111 Israeli victims from Palestinian attacks and 9,036 Palestinian victims from Israeli attacks. Neither Israeli nor Palestinian attacks show a strong clustering on weekdays compared to weekends. Victims from Palestinian attacks are evenly distributed over months while Israeli attacks are clustered in January and July, which is primarily driven by the Israeli operations *Cast Lead* and *Pillar of Defense* that took place during those months.

Table 1: Conflict Fatalities and U.S. 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 Defence (14nov2012-21nov2012)	Op. PoD-Op. DaPE (22nov2012-7jul2014)	Operation Defensive and Protective Edge (8jul2014-26aug2014)	Post Op. DaPE (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 inc. 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 inc. 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 inc. 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
Non-violent 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 09-29-2000 – 12-31-2016, including the 9/11 period. The upper panel of the table shows descriptive statistics for both Israeli and Palestinian fatal attacks split into 8 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 U.S. 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 U.S. mass media coverage of the Israeli-Palestinian conflict, we collect information from the evening news on three main 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.

Between 2000 and 2016, VTNA contains more than 15,000 evening news broadcasts and more than 200,000 individual news stories. For each individual news story, VTNA provides a headline, a summary, the length in seconds, as well as 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 first identify 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 which 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.[13] This gives us 314 news segments exclusively focusing on Israeli violence, 387 news segments exclusively focusing on Palestinian violence, 530 segments mentioning violence on both sides and 516 news segments which does not mention violence between the groups at all. Appendix Table A3 gives five examples of news stories and the 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 are 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 in 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 US.

[13] 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.

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 percent 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 nine out of ten days during Operation Pillar of Defense. However, during the three year period between these operations, the conflict was covered only once every twenty 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 extraordinary intensive fighting in the Gaza Wars of 2008/2009 and July 2014. The figure shows that our measure of conflict news correlates strongly with conflict fatalities, but also shows 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 are fewer in the later period. While the period of the Second Intifada, roughly 2000 to 2005, exhibits substantial turbulence and victims on both sides, the period after the first Gaza War is 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 Palestinian victims from Israeli attacks significantly increase reporting on Israeli violence and reporting on violence from both sides, but has no effect on non-violent conflict news. An Israeli attack with 9 Palestinian fatal victims (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 and strong, negative significant effects on exclusive reporting of Israeli violence and non-violent conflict news. A Palestinian attack with 1.2 Israeli fatal victims (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 indicate that attacks today and yesterday are particularly important for conflict news coverage.

The percentage of explained variation ranges from 7% for non-violent 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 only

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, DOW)	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 length of conflict news in minutes categorized by content. Independent variables are the number of fatal victims from Israeli and Palestinian attacks, respectively. 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 weekday fixed effects, and a set of controls for holidays and events which are presented in Section 4.1. All models are estimated using OLS, with Newey West standard errors allowing for autocorrelation of up to seven lags in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

include fixed effects and control variables. For reporting on Israeli violence we find that the share of explained variation increases by 16 percentage points, for Palestinian violence by 27 points and for violence on both sides by 22 points. For non-violent 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.

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, U.S. mass media covers events in the conflict not reflected in the number of fatalities, such as rioting and non-fatal 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 hate crime using two types of data described in detail in the preceding sections. The first is based on conflict fatalities. Our data allows us to distinguish between the identity of the attacker and the victims and we use this to examine through what mechanism conflict fatalities trigger hate crime. We hypothesize that fatal aggression generates more hate crime 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 primarily increase toward the attacker. To test this, we estimate the following equation:

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

where $Hate_{tk}$ is the number of hate crimes towards 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 analogous effect of attacks from the Palestinian side. In our main specification, we focus on the effects of attacks today and yesterday, since the media analysis, presented in Table 5, suggests that fatal attacks primarily increase conflict news today and yesterday. Theoretically, including one lag of fatalities allows enough time for potential offenders to be reached by, and react to, information about the event. The six-to-ten hour time difference between the U.S. 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 U.S. west(east) coast the previous day. Since we do not have information on the time of the day that 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. Due to the same reason, the time difference enables a response in the U.S. on the same calendar date as the conflict event. However, we present various alternative lag structures in the Appendix. $\boldsymbol{\omega}_t$ denotes a vector of control variables, which we explain in detail in Section 4.1. We include fixed effects for 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 U.S. increased during our period for unrelated reasons, or if both attacks and hate crimes are more common during certain calendar months or weekdays. ϵ_t is the idiosyncratic error term. As our dependent variable is count data and exhibit 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 7 lags.

Second, we estimate the effect of the conflict on hate crimes using U.S. mass media coverage of the conflict categorized by the attacker. Specifically, we estimate the following equation:

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

where β_I^k denotes the effect of the average length of conflict news focusing 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.

We test whether the effects of attacks and news are asymmetric, meaning that primarily the ethno-religious group associated with the attacker becomes a target of hate crime, by comparing the effects both across the attacker, holding the hate crime category constant, and across hate crimes, holding the attacker constant. Specifically, for hate crime k, we test whether $\alpha_I^k = \alpha_P^k$ and $\beta_I^k = \beta_P^k$. This addresses whether, for example, Israeli and Palestinian attacks have the same effect on anti-Jewish hate crime. For attacker i, we test whether $\alpha_i^{jew} = \alpha_i^{isl}$ and $\beta_i^{jew} = \beta_i^{isl}$. This addresses whether, for example, Israeli attacks have the same effect on both anti-Jewish and anti-

Islamic hate crimes. To test effects across hate crimes categories, we estimate Equation 1 and 2, respectively, as a system of seemingly unrelated regressions across the two hate crime categories.

Several important differences between the conflict fatalities and the conflict news measures are worth stressing. First, the context of the attack, not captured by the number of fatalities, may affect both reporting and any behavioral response. Our media variables capture the general newsworthiness of conflict events to a U.S. audience better than a fatality count. Second, conflict events are unlikely to trigger hate crimes if potential offenders never learn about them. The media variable is better at capturing the degree to which U.S. 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 fatalities from one side. Third, the media measures capture attacks and violence that are not fatal, such as rocket attacks, failed suicide bombings and kidnappings. Fourth, by categorizing conflict news according to which side is the attacker, we also get a measure of non-violent conflict news, which we use to test the effect of general conflict salience on hate crimes. Naturally, we cannot disentangle the effect of conflict news from the conflict events themselves. Nor can we exclude that conflict information reaches potential perpetrators through other information channels. For example, such individuals may receive information on events in the conflict through alternative media sources focusing on the middle east (e.g. Al Jazeera), social media, or personal contacts in the region.

4.1 Controls

The identifying assumption underlying a causal interpretation of the estimates is that the timing of fatal attacks and conflict news are exogenous with regards to the timing of anti-Jewish and anti-Islamic hate crime in the U.S. To control for potential omitted variables that may affect both hate crimes and the timing of attacks, we include in all specifications controls for religious holidays, U.S. news pressure and U.S. political events that drive it, as well as federal holidays.

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 U.S., which in turn may affect the level of hate crime. This can lead to a spurious correlation between conflict events and anti-Jewish and anti-Islamic hate crime. We therefore include a set of controls for Jewish, Israeli, Islamic and Palestinian holidays and events, listed in Appendix Table A4.

Durante and Zhuravskaya (2018) show that Israeli attacks are more likely to occur the day before U.S. news is dominated by important predictable events. The increased news pressure caused by the predictable events decreases the media coverage of the conflict. 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. We consider three examples of strategic timing. First, consider the case where attacks are timed to political events in the U.S., 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 levels of hate crime. In this case, the estimated effect of fatalities on hate crime could be biased either upwards or downwards, while the estimated effect of conflict news on hate crime will be biased upwards. Third, consider again the same strategic timing, but where the predictable events are associated with lower levels of hate crime. In this case, the estimated effect of both fatalities and conflict news on hate crime will be biased downwards. To address this concern, we control for major political and sports events which are *ex ante* predictable, generate higher levels of news pressure, and are themselves unlikely to trigger news reporting on the conflict. The events included are listed in Appendix Table A4.[14]

To further address this concern, we directly control for U.S. news pressure today and tomorrow. 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. The time constraint given by the fixed 30 minute time slot on these broadcasts allows us to measure the presence of newsworthy events. The more important an event is considered, the longer the news segment will be and the earlier in the broadcast the story will occur. We define *News pressure* as the time allotted to the top three news stories unrelated to Israel or Palestine in the evening newscast on ABC, CBS and NBC.[15]

Despite the above controls, conflict events may coincide with days or periods in which the level of hate crime in the U.S. is systematically different. For example, attacks may be timed to Christian or Federal holidays if holidays affect news consumption levels or the propensity for politicians to immediately react to controversial attacks. If such holidays are associated with systematically different levels of hate crimes, this will bias the estimates. We therefore control for a set of Christian and Federal holidays, as well as the yearly 9/11 anniversary. These holidays

[14]To select the predictable political events for our period, we use historical snapshots in the digital archive Wayback Machine (http://www.archive.com/web/; accessed November 11, 2018) of a forward-looking U.S. political calendar (http://www.politics1.com/calendar.htm; accessed November 11, 2018.). We also collected dates of major sport events, both in the U.S. 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 US. 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.

[15]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.

and events are listed in Appendix Table A4.

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, but that there are no effects of Israeli attacks on anti-Muslim hate crimes nor Palestinian attacks on anti-Jewish 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%.[16]

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

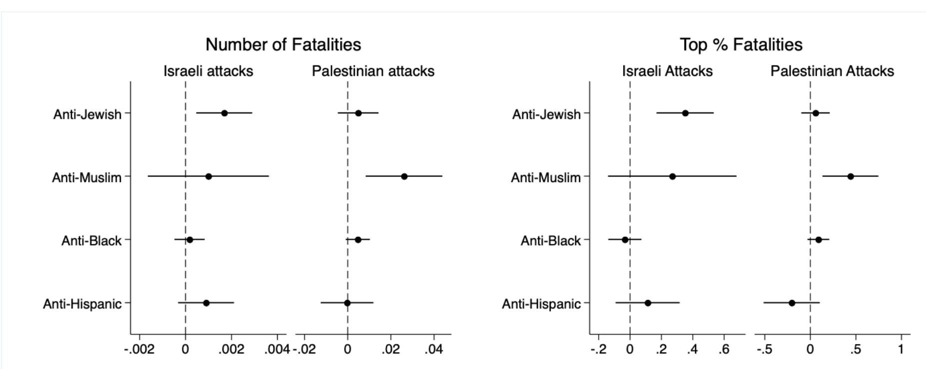
Table 3: The Effect of Conflict Fatalities on Hate Crime

	(1) Anti-Jewish	(2) Anti-Islamic	(3) Anti-Jewish	(4) Anti-Islamic	(5) Conflict News	(6) Conflict News
Victims Israeli attacks (t and t-1)	0.002**	0.001			0.029**	
	(0.001)	(0.001)			(0.010)	
Victims Palestinian attacks (t and t-1)	0.005	0.026**			0.129***	
	(0.005)	(0.009)			(0.015)	
Top 1% Israeli attacks (t and t-1)			0.351***	0.269		3.502***
(>40 victims, 57 dates)			(0.093)	(0.209)		(0.299)
Top 1% Palestinian attacks (t and t-1)			0.056	0.440**		1.729***
(>10 victims, 46 dates)			(0.080)	(0.157)		(0.209)
Smaller Israeli attacks (t and t-1)			0.032	0.047		0.651***
(1-40 victims, 2635 dates)			(0.023)	(0.051)		(0.125)
Smaller Palestinian attacks (t and t-1)			0.032	0.066		0.623***
(1-10 victims, 639 dates)			(0.034)	(0.075)		(0.121)
FEs (year, month, DOW)	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	5763	5763	5765	5765	5698	5700
Mean dependent var.	2.366	0.452	2.368	0.452	0.246	0.247
Sd. of dependent var.	1.843	0.732	1.845	0.732	0.894	0.894
Model	ML NB	ML NB	ML NB	ML NB	ML NB	ML NB
Pseudo R-squared	0.031	0.051	0.032	0.051	0.224	0.231
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 1,3) and Muslims (columns 2,4), and the length of conflict news reporting (column 5-6). The independent variables are the total number of victims the past two days from Israeli attacks and Palestinian attacks (columns 1, 2 and 5) and two mutually exclusive dummy variables indicating smaller and top percentile Israeli and Palestinian attacks (columns 3,4 and 6). All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey-West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis. The last three rows present the p-values of a test for equality between either 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 equivalence between the coefficients 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 figures show coefficient estimates on anti-Jewish and anti-Islamic hate crimes corresponding to columns 1-4 in Table 3 in addition to estimates on anti-Black and anti-Hispanic hate crimes included for comparison.

Columns 3 and 4 examine whether large attacks are driving the results, by regressing hate crime 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. By doing so, we relax the assumption of a linear effect of fatalities on hate crimes. This yields an indicator for 57 dates with more than 40 fatal Palestinian victims and 46 dates with more than 10 Israeli victims. 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. The reference category is days with no attacks. The results follow the same pattern. Israeli attacks trigger hate crimes against Jews and Palestinian attacks trigger hate crimes against Muslims. However, we only find significant effects for large attacks. A large Israeli attack increases anti-Jewish hate crimes by 35% and a large Palestinian attack increases anti-Muslim hate crimes by 44%. The effect of smaller attacks is not only insignificant, but the point estimates are 10 times smaller for Israeli attacks and 6 times smaller for Palestinian attacks. In Appendix Table A6, we show that the results are virtually the same when we partition the dummy indicating smaller attacks into additionally two categories.

To alleviate concerns that the effect of conflict fatalities on anti-Jewish and anti-Islamic hate crimes are spurious and, for example, induced by seasonal variation not captured by the fixed effects or our controls, we use two placebo hate crime categories as dependent variables: anti-Black and anti-Hispanic hate crimes. We present these results, using the same specification as in Table 3, in Figure 3 for comparison as well as in Appendix Table A7. The results show no significant effects of conflict fatalities on anti-Black and anti-Hispanic hate crime. In addition, the point estimates are much smaller compared to the effects we find for anti-Jewish and anti-Islamic hate crimes. This suggests that our main results are not driven by seasonality effects or time trends in reporting of hate crimes, strengthening the causal interpretation of the results.

Appendix Table A5 shows results from Equation 1 when using as the independent variables the number of conflict fatalities from either Palestinian or Israeli attacks on day t, and then gradually introducing up to five lags of the independent variables. The results show that anti-Jewish hate crimes are primarily triggered by victims from Israeli attacks and anti-Islamic hate crimes seem to be triggered by fatalities from both sides. This relationship first appears with the inclusion of the first lag of fatalities, and is robust to the inclusion of more lags as is evident from their joint significance.

When testing against the null, we find an asymmetric pattern in the effect of fatal attacks on hate crimes. Israeli attacks increase anti-Jewish hate crimes and Palestinian attacks increase anti-Islamic hate crimes. The bottom three rows of Table 3 present p-values for statistical tests of equivalence between coefficients between attackers and within hate crime categories. We first estimate the models in column 1 and 2 using seemingly unrelated regression and test for equivalence of the effect of Israeli and Palestinian attacks, respectively, across hate crime categories. We can reject the null of no difference in the effect of Palestinian attacks on anti-Jewish and anti-Islamic hate crimes, although we cannot reject the null for Israeli attacks. This result holds when we perform the same test for our non-linear specifications in column 3 and 4. In the last row, we test for the equivalence between the effects of victims from Israeli and Palestinian attacks within hate crime categories. For our linear specification, we can reject the null of no difference between Israeli and Palestinian attacks on anti-Islamic hate crimes, but not for anti-Jewish hate crimes. When we perform the same test for our non-linear specifications, we find that the effect on anti-Jewish hate crimes of large Israeli attacks are significantly larger than the (insignificant) effect of Palestinian attacks, whereas we cannot reject the null of no difference between the corresponding coefficients on anti-Islamic hate crimes. These results, in sum, suggest that the identity of the attacker matters for conflict spillovers in the U.S. Yet, despite that we do not find a significant effect of Israeli attacks on anti-Islamic hate crimes when testing against the null, we are cautious to rule out such an effect, especially in light of the results from the seemingly unrelated regressions. Our failure to reject the null of equivalent effects of Israeli attacks might reflect conflict dynamics that escape our statistical model. Specifically, existing research shows that the IDF systematically retaliates fatal Palestinian attacks, while Palestinians attack more randomly (Jaeger and Paserman, 2008 but see also Haushofer, Biletzki and Kanwisher, 2010). Thus, it is possible that Israeli attacks are correlated with events in the conflict that trigger anti-Islamic violence, not captured by our fatalities data, which would bias the effect of Israeli attacks on anti-Islamic hate crime upwards.

Finally, we examine how conflict fatalities affect the length of conflict news reporting. We show these results in columns 5 and 6 in Table 3. We find strong and significant effects for both Israeli and Palestinian attacks for both types of measures. As expected, large attacks result in much longer news reporting compared to smaller attacks. An Israeli attack in the top percentile increases conflict news reporting by approximately 3.5 minutes, while the analogous Palestinian attack increases conflict news reporting by 1.7 minutes. These relative magnitudes are inverted when we look to the effect of the linear measure of fatalities, where one fatality from a Palestinian attack leads to more news reporting compared to a fatality from an Israeli attack. This may reflect that Palestinian attacks are less common and, therefore, deemed more newsworthy. In contrast to the effect on hate crimes, we find significant effects of smaller attacks on conflict news reporting. The next section turns to the effects of conflict news reporting on hate crime.

5.2 The Effect of Conflict News on Hate Crime

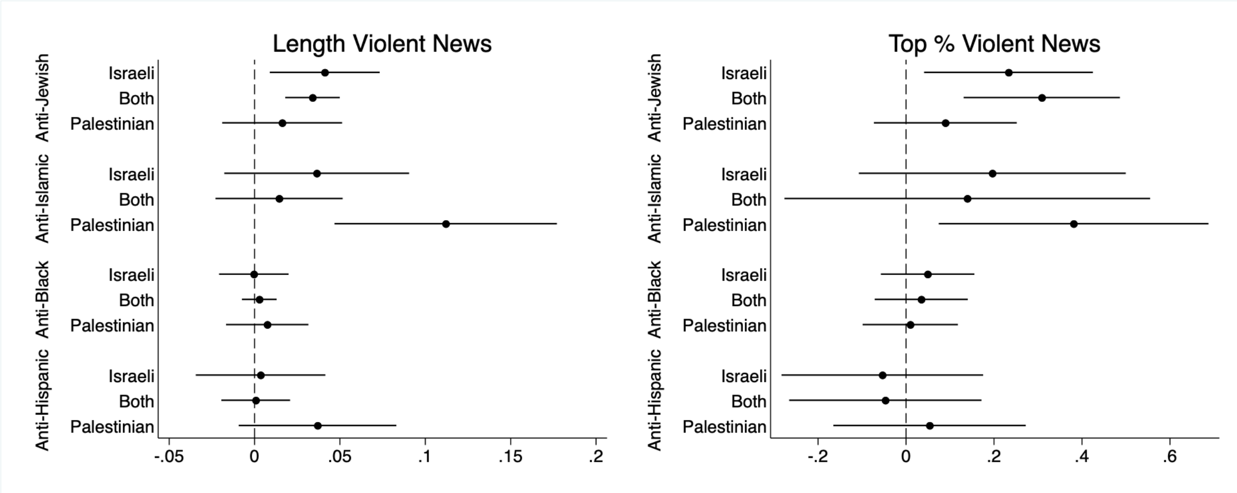
This section examines how hate crimes change after U.S. mass media coverage of violence from each party in the conflict. We estimate Equation 2 using as the independent variables the length of conflict coverage, today and yesterday, on Israeli violence, Palestinian violence, and violence from both sides respectively.

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, today and yesterday, 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, today and yesterday, 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, today and yesterday, 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, DOW)	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 weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. The last three rows present the p-values of a test for equality between either the effects of (extensive) reporting on Israeli or Palestinian attacks on anti-Jewish and anti-Islamic hate crimes estimated using seemingly unrelated regressions, or a test for equivalence between the coefficients for reporting on Israeli and Palestinian attacks within the same model. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Figure 4: News on the Israeli-Palestinian Conflict and Hate Crimes



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

Columns 1 and 2 of Table 4 regress anti-Jewish and anti-Islamic hate crimes on the length of conflict news, today and yesterday, covering either Israeli attacks, both sides attacking, or Palestinian attacks. Column 1 shows that anti-Jewish hate crimes are triggered by news coverage involving Israeli attacks, regardless of whether the coverage 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. The effect of news focusing exclusively on Palestinian attacks is much smaller and we cannot reject the null of no effect. In Column 2, we see no indication that coverage involving Israeli violence is triggering hate crimes towards Muslims, but rather 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%.

Similar to our analysis of conflict fatalities, we relax the linearity assumption by regressing hate crimes on two dummies for each type of coverage, indicating whether the conflict news reporting is in or below the top percentile. The results show the same pattern as in column 1 and 2. On days when news reporting is in the top percentile of the distribution of reporting on Israeli attacks or both sides attacking, respectively, anti-Jewish hate crime is expected to increase by 26% and 36% respectively. The effect of extensive reporting on Palestinian attacks is much smaller and again, we cannot reject the null of no effect. Column 4 mirrors the results in Column 2, showing that Anti-Muslim are triggered by extensive reporting on Palestinian attacks. The coefficient suggests that extensive reporting on Palestinian attacks is expected to increase anti-Muslim hate crimes by 46%. Looking at the effects of news reporting below the top percentile, we see that the point estimates are much smaller and for the most part insignificant. The exception is the coefficient for coverage in bottom 99 percentiles of both sides attacking, which shows a significant effect on anti-Jewish hate crimes. In Appendix Table A10, we show that these results are robust to splitting the dummy for news reporting below the top percentile into one additional category. Figure 4 and Appendix Table A9 once again show that anti-Black and anti-Hispanic hate crimes are not affected by conflict news reporting.

Similar to our analysis of conflict fatalities, Appendix Table A8 presents the results of regressing the number of hate crimes on day t on the length of conflict reporting the same day, and subsequent columns gradually introduces one, two and five lags of the independent variables. Column 1 indicates that news on Israeli attacks or both sides attacking triggers hate crime towards Jews the same day. Gradually adding lags reduces precision of individual estimates, but the F-test shows that the lags for coverage of both sides attacking are statistically different from zero. Columns 5-8 shows similar results for anti-Muslim hate crimes. Coverage of Palestinian attacks seem to primarily trigger hate crimes the same day.

Overall, the results in Table 4 suggest that general salience of the conflict in U.S. mass media is not sufficient to trigger hate crimes against American Jews or Muslims. Instead, it depends on if the coverage is focusing on Israeli or Palestinian violence. As in our analysis of conflict fatalities, we formally test the equivalence of the coefficients across and within hate crime categories. The p-values for these tests are reported in the bottom panel of Table 4. Comparing across hate crime categories, we can reject the null of no difference between the effects of length of coverage on Palestinian attacks, but not for coverage involving Israeli attacks or any of the coefficients on top 1% news reporting. These results are, thus, consistent with the effect of fatal attacks. Comparing coefficients within models and hate crime categories, we can reject the null of no difference between the effects on anti-Islamic hate crimes between the length of coverage of Israeli attacks and Palestinian attacks, but not for anti-Jewish hate crimes. For the top percentile news coverage, we cannot reject the null for either hate crime category.

5.3 Heterogeneity of Media Reporting and Hate Crimes

This section uses our conflict news measures to gain further insights on why the conflict increases hate crimes and on 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 non-violent conflict reporting affect hate crimes? Fourth, does the conflict affect violent as well as non-violent hate crime?

We first examine if smaller attacks, that still receive media coverage, induce hate crimes. In column 1 and 3 of Table 5, we regress anti-Jewish and anti-Islamic hate crime on our linear measures of conflict reporting but exclude days that have had an attack in the top percentile from either side sometime during the past week. We see that the effects of Israeli violence and violence from both sides on anti-Jewish hate crimes remain and actually increases slightly compared to the estimates in Table 4. The same is true for the effect of Palestinian violence on anti-Islamic hate crimes. This suggests that attacks below the top percentile trigger hate crimes, conditional on that they are covered in news.

Second, we proceed to examine if the effect of news on conflict violence can be generalized to other conflicts. Specifically, our news data contain reporting on the 2006 Israel-Lebanon war. The 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 and anti-Islamic hate crimes. The intensity and brevity of the war makes 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%. This shows that the effect of conflict spillover we identify for the Israeli-Palestinian conflict extends to the broader Arab-Israeli conflict.

Third, we address whether non-violent conflict news may also affect hate crimes. Our main results show that attacks and conflict reporting on violence primarily triggers hate crimes against the ethno-religious group associated with the attacker. This suggests that general conflict news have little effect on hate crime. We test this directly by examining the effect of *non-violent conflict news*, which measures the coverage of the Israeli-Palestine conflict excluding all reporting on violence. The results are presented in Column 2 and 4 of Table 5. We find no evidence that non-violent news coverage of the Israeli-Palestinian conflict induces anti-Jewish or anti-Islamic hate crime. 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 non-violent 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 does not only trigger less severe forms of hate crimes, such

Table 5: Effects of Different News Content on Hate Crime

	(1) Anti-Jewish	(2) Anti-Jewish	(3) Anti-Islamic	(4) Anti-Islamic
Israeli Violence (t and t-1)	0.048*	0.042**	0.026	0.038
	(0.020)	(0.016)	(0.038)	(0.027)
Both Violence (t and t-1)	0.055**	0.034***	0.080	0.013
	(0.021)	(0.008)	(0.045)	(0.019)
Palestinian Violence (t and t-1)	-0.010	0.017	0.132*	0.113***
	(0.037)	(0.018)	(0.059)	(0.033)
Non-Violent Conflict News (t and t-1)		-0.013		-0.000
		(0.019)		(0.037)
Israel-Lebanon Violent Conflict News (t and t-1)		0.015*		0.021*
		(0.007)		(0.009)
FEs (year, month, DOW)	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 only includes 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 weekday fixed effects and are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

as property crimes and vandalism, but increases violence toward Jews and Muslims in the U.S. Table 6 estimates the effect of fatal attacks and news coverage on violent and non-violent hate crimes respectively. Columns 1-2 show that Israeli attacks trigger both violent and non-violent anti-Jewish hate crimes. Columns 3-4 show the results for anti-Islamic hate crimes. Palestinian attacks trigger violent anti-Muslim hate crimes, while the coefficient for non-violent 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. Column 5-6 show that news coverage of Israeli violence or violence on both sides trigger both violent and non-violent anti-Jewish hate crimes. However, the effect of Israeli violence on non-violent 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 non-violent anti-Muslim hate crimes is only significant at the 10% level.

Table 6: Effect on Violent and Non-Violent Hate Crimes

	(1) Violent Anti-Jewish	(2) Non-Violent Anti-Jewish	(3) Violent Anti-Muslim	(4) Non-Violent Anti-Muslim	(5) Violent Anti-Jewish	(6) Non-Violent Anti-Jewish	(7) Violent Anti-Muslim	(8) Non-Violent Anti-Muslim
Number of victims, today and yesterday, 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, today and yesterday, 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, DOW)	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 non-violent (columns 2 and 6) anti-Jewish hate crimes and violent (columns 3 and 7) and non-violent (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 results. Specifically, we focus on the sensitivity of the effect of top percentile attacks and news reporting. The overall findings are unaffected by the choice of controls and are not driven by specific conflict periods, U.S. states, temporal variation in police agencies' participation in the Uniform Crime Reporting Program, or the choice of model specification or lag structure. They are also relatively unaffected when adding future attacks and reporting to the model.

First, Appendix Table A11 estimates the effect of conflict news and conflict fatalities on hate crime while adding one set of temporal controls at a time. The table shows that the findings are not dependent on including a specific set of control variables.

Second, Appendix Table A12 splits the sample into four particularly intense conflict periods and estimates the effect of conflict fatalities and conflict news today and yesterday on hate crime. We exclude the conflict periods one at a time. This addresses whether our findings are predominantly driven by specific conflict periods and whether the effect sizes differ across conflict periods. The conflict periods are the Second Intifada, Operation Cast Lead, Operation Pillar of Defense and Operation Protective Edge, further described in Section 3.2. 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 conflict periods, but there is some variation in the point estimates. For instance, excluding operation Protective Edge, accounting for 25% of all fatalities from Israeli attacks, reduces the point estimates and precision somewhat. Similarly, 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 slightly more sensitive to excluding the Second Intifada compared to the effect of fatalities, but the effects are largely unaffected by dropping the other conflict periods. This is perhaps not surprising, since the Second Intifada accounts for 62% of all conflict coverage. Dropping the Second Intifada strongly reduces the precision for all types of news reporting that are significant in the full sample 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. We speculate that this might reflect the fact that most of the larger attacks from the Palestinian side occur during this period, and that attacks after occur mostly in conjunction with Israeli attacks. In Appendix Table A13, 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 effects on anti-Islamic hate crimes are only significant at the ten percent level when dropping either the Second Intifada or Protective Edge. In sum, the results from Appendix Tables A12 and A13 show that the main results are not driven by a single conflict period in our sample, but suggest that there may be heterogeneity in the effect sizes across conflict periods.

Third, we further probe the sensitivity of the results by dropping certain U.S. states from the sample. Appendix Table A14 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 effect of Israeli attacks on anti-Jewish hate crime, and Palestinian attacks on anti-Islamic hate crime, is 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 turns 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.

Fourth, Appendix Table A15 estimates our main specifications using ordinary least squares 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 crime on that day. Presented in the columns 3-6 in both panels, we see that both OLS models show similar results as our main results, which are shown 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 non-significant effect of coverage of Palestinian attacks.

Fifth, Appendix Table A16 estimates our main linear specifications using either weekly level data (columns 1-4) or daily level data but with our independent variables aggregated the past 3 days instead of 2 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 primarily seem to trigger anti-Jewish hate crimes, while Palestinian attacks primarily seem to trigger anti-Muslim hate crimes, although the coefficient estimate decreases somewhat and becomes insignificant in the daily level data with 3 day aggregates.

Sixth, an additional threat to the identification strategy would be if agencies select in and out of the Uniform Crime Reporting Program in response to events in the conflict. Appendix Table A17 replicates our main specifications using only data from agencies that do not drop out of the program once they start participating. Our findings replicate on this sample, and are, if anything, more pronounced compared to the full sample.

Seventh, Appendix Tables A18-A19 present how our main results are affected when including future large attacks in the model. The conflict dynamics, with its retaliatory pattern and extreme periods of intense violence, is likely to make future fatalities outcomes of our treatment variable. The conflict events that make the conflict flare up and generate more fatal attacks may also be the events that trigger hate crimes in the US. In such a case, the number of fatalities a particular attack today generates in the following days might be a reasonable proxy for the contentiousness of the attack, or the intensity of the conflict today, as compared to the number of fatalities generated today. If so, we would expect future large attacks to also predict hate crimes today, or at least attenuate the effect of previous attacks when including them in the model. However, as Appendix Tables A18-A19 demonstrates, our main estimates of the effect of large attacks and extensive media reporting is somewhat smaller but relatively unaffected by adding future attacks in the model.

5.5 Retaliatory Motive or Conflict Salience?

The overall results are consistent with the interpretation that hate crimes in our setting are driven by some kind of retaliatory motive among perpetrators. Since we do not have data on who the perpetrators are and, in addition, since offender motives are not observable but can only be inferred, we cannot completely rule out all alternative explanations for why the conflict triggers hate crimes. However, several of our results are inconsistent with alternative explanations. First, the effect does not seem to be driven by particularly violent events in general, or news reporting on them, as we find no effect on other hate crimes categories. Second, general salience of the Israeli-Palestinian conflict is in itself insufficient for triggering hate crimes. This is evident by the insignificant effect of non-violent conflict news, reported in Section 5.3. Third, the asymmetric effects of both attacks and reporting on conflict violence, reported in Sections 5.1 and 5.2, further suggest that general conflict violence or reporting does not trigger hate crime. Although we could not reject that the effect of Israeli attacks and reporting on Israeli violence was significantly different across anti-Jewish and anti-Islamic hate crimes, we find that the identity of the attacker matters for whether Jews or Muslims are subject to hate crimes. We only find significant effects of attacks on the religious group associated with the attacker. Taken together, this emphasizes the importance of the type of conflict event or news reporting as opposed to the general intensity of fighting or reporting for triggering hate crimes. Specifically, this suggests that perpetrators are driven by some form of retaliatory motive and that they are attached to conflict actors, in one form or another. An alternative interpretation, which need not be mutually exclusive, is that violent conflict news, and in particular news on violence committed by a specific actor, more effectively triggers pre-existing animosity primarily towards groups associated with that specific actor.

6 Concluding Remarks

We document that social identity ties facilitate the spread of violent conflict. Using daily data on conflict fatalities and U.S. news coverage of the conflict between 2000-2016, we examine if the Israeli-Palestinian conflict causes hate crime towards Jews and Muslims in the U.S. 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. However, we find no effect of non-violent 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 among perpetrators, inducing violent behavior against American Jews and Muslims. While news reporting both in the U.S. and Europe have indicated that the Israeli-Palestinian conflict may trigger anti-Jewish hate crime, there has been little reporting on how the conflict affect Muslims living outside of the conflict vicinity. Recently, however, U.S. news media have reported on both anti-Muslim and anti-Jewish hate crimes with a clear connection to the 2021 Israeli-Palestinian crisis.[17]

We speculate that social identity ties are likely to have an even larger role in the transmission of violence in settings where civil conflict or larger scale violence are at risk. The reason is that animosity directed at groups with identity ties to foreign conflict actors are likely to interact with, and possibly amplify, other channels through which conflicts might spill over. For example, co-ethnics involved in conflict abroad might provide important information and inspiration for how to increase political power in the domestic scene by mobilizing along ethnic lines. Such information diffusion might be more effectively transmitted through a lens of inter-ethnic animosity and hatred. The emotional response to inter-ethnic animosity might also facilitate such mobilization by galvanizing members of these groups into action. Our documented mechanism might also interact with spill-over mechanisms unrelated to identity ties. For example, inter-ethnic animosity and violence might boost the demand-side of regional markets for violence. This might in turn facilitate the cross-border activities of violent underground actors – such as warlords, terrorist organizations, or organized crime – that often operate on the supply-side of such markets, and which are recognized as major sources of regional instability (Silve and Verdier, 2018). An impor-

[17]See 'Death to Palestine' spray painted on Brooklyn mosque, ABC7 NY, 05-13-2021, accessed 05-21-2021, and Antisemitic incidents heightened across U.S. amid Israel-Gaza fighting; mosques were damaged, too, NBC News, 05-21-2021, Accessed 05-24-2021.

tant endeavor for further research is to understand how and under what conditions the spread of inter-group animosity is important for conflict contagion.

Indeed, there are strong reasons to believe that the cross-border spread of animosity through identity ties could have important ramifications beyond violent and criminal behavior. For example, it might deteriorate inter-group trust 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 inter-group 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, 2019). Animosity directed towards a certain minority can also have long-term effects on the groups' rate of assimilation, labour market participation, and ethnic identification (Gould and Klor, 2016). Mitts et al. (2019) provides an extreme example, where anti-Muslim hostility in Europe might have increased Muslim radicalization and support for ISIS.

As news and social media reporting becomes ever more rapid, individuals all over the globe can take part of violent conflict events in real time. Research 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. Hence, an important future research agenda is whether the extent and type of mass media reporting might be significant for the spread of violence. Perhaps this is even more important for largely unmoderated social media content, which has been suggested to fuel inter-group animosity and violence in, for example, Myanmar and the Philippines.

We show that conflict can have violent spillovers and that victimization can transcend the conflict locality. There are reasons to believe that the spillover effects of conflicts are not restricted to violent and criminal behavior but are far more encompassing. With increasing migration and technological advancement, the consequences of regional conflicts may, thus, become less bounded to the vicinity of the conflict.

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7 Appendix

Table A1: Seasonal Variation in Hate Crimes, Conflict Victims and Conflict News 2000-2016 Excluding 6 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 09-29-2000 – 10-09-2001 and 01-03-2002 – 12-31-2016. 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* 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 weekday 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 splits the conflict news variable into four categories, explained further in section 3.3.

Table A2: Hate Crimes Against Jews and Muslims 2000-2016, Excluding 6 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
Non-Violent 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 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 Guidelines (2018). *Observations* 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 09-29-2000 – 10-09-2001 and 01-03-2002 – 12-31-2018.

Table A3: 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	NA
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 are filtered out from all news stories that appear on the thirty 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, Jerusal, 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 Palestinian reference, 2) the headline contains an Israeli reference and the summary a Palestinian reference, 3) the headline contains a Palestinian reference and the summary an Israeli reference. Row 1 and 2 are examples of stories that are filtered out, and row 3-5 are examples of stories that are included based on the three word filters.

Table A4: 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/Israeli'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 primary, 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. The selection of holidays and events is described in Section 4.1.

Table A5: 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, DOW)	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 column 1 and 5, the independent variables are the total number of victims from an attack from the respective sides at day t. Subsequent columns add up to 5 lags of the independent variables, where column 4 and 8 includes the total fatalities from attacks from the respective sides at t to t-5. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are 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 parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Table A6: Non-linear 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, DOW)	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 52th to the 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 towards Jews and Muslims, respectively. In column 3, the independent variable is a dummy for any conflict news. Column 4 uses as independent variable the length of conflict news, while columns 5-7 uses conflict reporting focusing respectively on either Israeli violence, violence from both sides, or Palestinian violence. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. Columns 1-2 are estimated using a maximum-likelihood negative binomial model. Column 3-4 are estimated using OLS. Newey West standard errors allowing for autocorrelation of up to seven lags in parenthesis.

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

Table A7: 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, today and yesterday, 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, today and yesterday, 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, today and yesterday, 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, DOW)	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 1,3) and Hispanics (columns 2,4). 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 weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Table A8: 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, DOW)	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 U.S. 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 auto-correlation of up to seven lags presented in parenthesis.

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

Table A9: 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, today and yesterday, 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, today and yesterday, 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, today and yesterday, 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, DOW)	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 1,3) and Hispanics (columns 2,4). 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 weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.

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

Table A10: Non-linear 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, DOW)	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 variable indicates conflict news in the top percentile. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Table A11: Robustness Checks: Introducing Controls

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
Top 1% Israeli attacks, t and t-1	0.348***	0.348***	0.347***	0.351***	0.321***	0.265	0.279	0.285	0.270	0.258
(>40 victims, 57 dates)	(0.091)	(0.092)	(0.093)	(0.093)	(0.087)	(0.213)	(0.216)	(0.211)	(0.209)	(0.198)
Top 1% Palestinian attacks, t and t-1	0.071	0.056	0.057	0.056	0.045	0.434**	0.438**	0.442**	0.440**	0.410**
(>10 victims, 46 dates)	(0.079)	(0.080)	(0.080)	(0.080)	(0.079)	(0.153)	(0.157)	(0.156)	(0.156)	(0.155)
Smaller attacks from either side	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, DOW)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	-	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	Yes
Political events	-	-	Yes	Yes	Yes	-	-	Yes	Yes	Yes
News Pressure (t and t+1)	-	-	-	Yes	Yes	-	-	-	Yes	Yes
2 lags dep. var	-	-	-	-	Yes	-	-	-	-	Yes
Observations	5767	5767	5767	5765	5761	5767	5767	5767	5765	5761
Model	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	0.044	0.048	0.049	0.051	0.053

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
Top 1% Israeli Violence (t and t-1)	0.231*	0.227*	0.231*	0.233*	0.211*	0.216	0.220	0.206	0.196	0.177
	(0.097)	(0.098)	(0.098)	(0.098)	(0.093)	(0.150)	(0.152)	(0.151)	(0.155)	(0.153)
Top 1% Both Violence (t and t-1)	0.308***	0.316***	0.316***	0.309***	0.269**	0.108	0.133	0.137	0.139	0.100
	(0.091)	(0.091)	(0.091)	(0.091)	(0.086)	(0.216)	(0.213)	(0.210)	(0.212)	(0.208)
Top 1% Palestinian Violence (t and t-1)	0.080	0.090	0.092	0.089	0.080	0.380*	0.378*	0.373*	0.381*	0.388**
	(0.084)	(0.083)	(0.083)	(0.083)	(0.081)	(0.155)	(0.154)	(0.153)	(0.156)	(0.150)
Bottom 99% reporting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs (year, month, DOW)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	-	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	Yes
Political events	-	-	Yes	Yes	Yes	-	-	Yes	Yes	Yes
News Pressure (t and t+1)	-	-	-	Yes	Yes	-	-	-	Yes	Yes
2 lags dep. var	-	-	-	-	Yes	-	-	-	-	Yes
Observations	5635	5635	5635	5633	5631	5635	5635	5635	5633	5631
Model	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	0.038	0.047	0.048	0.050	0.053

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 today or yesterday, and in Panel B days with top percentile news reporting today or yesterday, 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 parenthesis.

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

Table A12: Robustness 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 vic. excluded fr. PA	0.000	0.756	0.008	0.005	0.062	0.000	0.756	0.008	0.005	0.062
Share vic. 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 today or yesterday, and in Panel B days with top percentile news reporting today or yesterday, split by type of violence reported on. Column 1 and 5 includes the whole sample period between 2000-2016, 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 weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.

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

Table A13: Robustness 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 today or yesterday. Column 1 and 5 includes the whole sample period between 2000-2016, 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 weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Table A14: Robustness 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, DOW)	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, DOW)	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 variable is 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 today or yesterday, and in Panel B days with top percentile news reporting today or yesterday, split by type of violence reported on. Column 1 and 4 exclude hate crimes in California, column 2 and 5 exclude hate crimes in the state of New Jersey, while column 3 and 6 excludes hate crimes in the state of New York. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Table A15: Robustness 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, DOW)	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, DOW)	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 today or yesterday, and in Panel B days with top percentile news reporting today or yesterday, split by type of violence reported on. The dependent variable is the either 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). Column 1 and 2 uses a maximum-likehood negative binomial model, columns 3-6 uses an OLS, and column 7-8 uses a Probit regression. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001

Table A16: Robustness 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
DOW 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 (Coverage of) Isr. Attack $\beta^{Jew} = \beta^{Isl}$	0.023		0.197		0.738		0.814	
P-value Coverage of both attacking $\beta^{Jew} = \beta^{Isl}$			0.224				0.154	
P-value (Coverage of) Pal. Attack $\beta^{Jew} = \beta^{Isl}$	0.033		0.224		0.264		0.154	

Note: The dependent variable is 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 collapses the data to weekly level and regresses the independent variables week t on the same week aggregates of hate crimes, controlling for year and calendar-month fixed effects. Columns 5-8 uses daily level data, but uses as independent variables the aggregate of the past 3 days. Models in the daily data set in columns 5-8 control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. The last two 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 auto-correlation of up to seven lags in the daily data set, and 4 weeks in the weekly data set.

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

Table A17: Agency Robustness

	(1) Anti-Jewish	(2) Anti-Muslim	(3) Anti-Jewish	(4) Anti-Muslim
Top 1% victims, today and yesterday, 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, today and yesterday, 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, DOW)	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 variable is 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 who, 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 weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags in parenthesis.

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

Table A18: 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, DOW)	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 today or yesterday, controlling for top percentile attacks day t+1 (tomorrow) up to t+3. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.

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

Table A19: 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, DOW)	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 today or yesterday, split by type of violence reported on, controlling for the analogous variables for top percentile conflict reporting day t+1 up to t+3. All models control for year, calendar-month and weekday fixed effects, as well as a set of controls for holidays, events, and news pressure which are presented in Section 4.1. All models are estimated using a maximum-likelihood negative binomial model with Newey West standard errors allowing for auto-correlation of up to seven lags presented in parenthesis.
* p <0.05, ** p<0.01, *** p<0.001