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1 Introduction

In his 2010 Andrew Olle Media Lecture, Alan Rusbridger, then the editor-in-chief of the Guardian said: *"News organisations still break lots of news. But, increasingly, news happens first on Twitter. If you're a regular Twitter user, even if you're in the news business and have access to wires, the chances are that you'll check out many rumours of breaking news on Twitter first. There are millions of human monitors out there who will pick up on the smallest things and who have the same instincts as the agencies—to be the first with the news. As more people join, the better it will get."*[1] Rusbridger's forecast is confirmed a decade later: social media has become an important tool for professional journalists. A series of annual surveys of journalists shows that, throughout the last decade, the majority of journalists in developed countries—including the US, the UK, and Germany—consider social media important for their work, whereas the share of those who claim that social media does not play any role remain in single digits (see, e.g., the reports by a media consulting firm Cision, 2011, 2012, 2013, 2016, 2017, 2020).

There is an agreement among media scholars that journalists from well-established traditional media outlets extensively use social media, and especially Twitter (e.g., Moon and Hadley, 2014). In particular, journalists use social media to access news in real time, measure the demand for news on different topics by what is trending, get feedback on their own work, and enlarge their audience (see, e.g., von Nordheim et al. (2018), who study the use of social media by reporters in The New York Times, The Guardian, and Süddeutsche Zeitung, or Lysak et al. (2012) and Adornato (2016), who analyze a nationwide survey of news directors of local TV stations in the US).

Increasingly, journalists and communication scholars point out that social media also transforms eyewitnesses of newsworthy events into "citizen journalists" (e.g., Patrikarakos, 2017; Singer and Brooking, 2018; Higgins, 2021). The posts of such citizen journalists on social media allow traditional journalists, open-source investigators, and the interested public to learn more details about newsworthy events, compared to what was possible before the emergence of social media. In particular, reporters get to see these events through the lenses of smartphones of eyewitnesses and participants of these events, when they cannot witness them first hand. This implies that citizen journalism could potentially change the perception of traditional-media reporters of the very events they need to cover. As a result, the way traditional journalists report the news could also change. Prior literature provides no systematic test of this conjecture and this paper tries to fill this gap.

We test whether and how information available on social media affects traditional-media reporting of conflicts. Our focus is on the conflict news because one should expect social media to have a more important impact on the traditional-media coverage of those topics, for which reporting is dangerous, events are unpredictable, and the sites of some of the events are inaccessible. Conflicts often satisfy all of these criteria (Creech, 2017).

[1] https://www.theguardian.com/media/2010/nov/19/alan-rusbridger-twitter, accessed March 8, 2021.

We estimate how the information available on social-media in Israel and Palestine, measured by the flow of tweets about the Israeli-Palestinian conflict from the conflict zone, affect news coverage of this conflict by the main US TV channels. For identification, we exploit an exogenous variation in posting on social media in Israel and Palestine stemming from local internet outages that occur as a result of technical failures as well as infrastructure damages caused by lightning strikes. We show that when social media is not muted by internet outages in the conflict zone, it causes larger conflict coverage on US TV, both in terms of extensive and intensive margin. More importantly, it also substantially changes the content and the tonality of conflict coverage. Social-media posts about the conflict from Israel and Palestine make US TV news about the conflict more emotional, particularly in the presence of Palestinian casualties, and have a significant impact on the topics of conflict-related broadcasts. When social media is not muted in the conflict zone, the conflict-related news stories on US TV focus more on portraying the suffering of civilians and less on the role of the US foreign policy or general political issues in conflict resolution.

A case study (presented in Section 6) illustrates our findings: It is a story of Farah Baker, a 16-year-old Palestinian girl, who tweeted in English from Gaza during the 2014 Gaza War (e.g., Patrikarakos, 2017, pp. 21-37). On Twitter, she documented the Israeli bombing raids that occurred around her home. She both shared her own footage of the attacks and described her emotions and thoughts. These tweets were noticed by the Western reporters who were covering the conflict. As a result, media all over the world reported on Farah and used the content of her Twitter account in their reporting. For example, Appendix Figure A1 shows the screenshots of CNN's news program that directly quoted the content posted by Farah Baker on Twitter.[2]

We focus on US television news about the Israeli-Palestinian conflict for several reasons: First, TV remains an important source of news for the American public despite the rise of social media. According to Pew Research Center, 46% of a representative sample of the US population preferred getting news from television in 2016; and 44% – in 2018 (Pew Research Center, 2018). Second, there is a considerable demand for news about the Israeli-Palestinian conflict in the US that is addressed by the media. For example, in 37% of all days with deadly attacks during 2009-2016, at least one story about the conflict zone appeared on one of the main US TV news channels (we describe the data below). Finally, actors on both sides of the conflict are present on social media and regard this presence as an important part of their strategy.[3]

[2]Figure A2 illustrates that US TV also uses tweets by the Israeli Defense Forces (IDF) and footage from other social media, namely, YouTube, as a source.

[3]In his book *War In 140 Characters: How Social Media Is Reshaping Conflict In The Twenty-first Century*, British journalist David Patrikarakos provides testimonies of representatives of both the IDF and Hamas with regard to their strategy of social-media presence (Patrikarakos, 2017). Former IDF international spokesman Lt. Col. Peter Lerner stated in his interview to Patrikarakos: *"If you're silent on social media, you are not putting anything in your enemy's way that prevents their message from gaining steam... And if you are silent on social media, you're not getting your own message across; and... not giving your supporters ammunition to use. My job is to prevent that from happening"* (p. 47). Patrikarakos also quotes Hamas spokesperson

Our empirical analysis combines several data sources. The main outcome variables come from the web-scraped TV News Archive. We use full transcripts of all news broadcasted by the following US TV channels: ABC, CBS, CNN, FOX, MSNBC, NBC, PBS, and Bloomberg. For comparison, we also use transcripts of news by Al Jazeera America, a Qatari TV network available in the US. Based on these transcripts, for each day and network, we first identify all news stories about the conflict zone based on stemmed keywords for Israel, Palestin, and Gaza. And, then, for each such news story, using various text-as-data techniques, we build measures describing the content of conflict-related news in terms of their emotional intensity and the topics covered by these news stories, normalized by their length. We, then, aggregate these measures to build daily series for each TV network of the extent, tonality, and topics of conflict-related news coverage.

To build a measure of social-media activity in the conflict zone—our main explanatory variable—we web-scraped the population of all tweets with stemmed keywords for Israel, Palestin, and Gaza. We, then, establish the language of each tweet and train a machine-learning algorithm to identify whether the topic of each English-language tweet is related to the conflict between Israeli and Palestinians. Using the self-reported user profile, we also identify the location of the user account, i.e., Israel, Palestine, or the rest of the world, and the type of the account, i.e., ordinary person, media representative, government official, organization, or business. Then, we construct daily series of the number of conflict-related tweets in English written by users in Israel and Palestine. We combine these data with daily data on potential determinants of news coverage of the conflict—fatal casualties on both sides, local weather conditions in the conflict zone, and the news pressure in the US—and with the main source of exogenous variation, the measures of local internet outages (described below). The resulting dataset covers the period from November 2009 to April 2016.

The key challenge in identifying the effect of social media on traditional-media reporting is identification: both reverse causality and omitted variables can explain the association between the content posted on social media and the news by the traditional-media outlets. To address this endogeneity problem, we use internet outages in the conflict zone as an instrument for social-media activity. This instrument predicts access of users in the conflict zone to all social media and other online media platforms. Therefore, we consider our main endogenous explanatory variable—tweets from the conflict zone—as an aggregator of all social-media activity in Israel and Palestine.

We consider two sources of internet outages: lightning strikes and technical failures. First, we use the data on the timing and location of all cloud-to-ground lightning strikes in the populated areas in Israel and Palestinian territories. Information-and-Communication-Technology (ICT) experts agree that electrostatic discharges generated by such lightning strikes can dam-

Ihab al-Ghussain who said during the 2014 Gaza War: *"it is not just about taking pictures of dead people... We're now telling [the story of] this family, and how they were eating breakfast when they were killed"* (p. 84). Similarly, the IDF's chief of New Media Lt. Sacha Dratwa described his work as follows: *"Facebook and Twitter are the battle fields. It is there that we fight, each and every day"* (as quoted by Israeli media, https://www.israelnationalnews.com/News/News.aspx/145247, accessed March 12, 2021).

age local ICT infrastructure and reduce user ability to connect to the internet in the absence of power-surge-protection tools (Zeddam and Day, 2014; Martin, 2016). Second, we rely on the methodology developed by computer scientists to detect internet outages by monitoring the traffic between a certain geographical area and the rest of the World Wide Web (WWW) (Dainotti et al., 2011; Padmanabhan et al., 2019). As there are always some active Internet Protocol (IP) addresses, many of which are automatic, a sudden decrease in traffic is a sign of an internet outage, generally caused by a local technical failure. We collected data on the amount of traffic directed to and from the Israeli and Palestinian Autonomous Systems (i.e., the collections of local IPs) and identified the timing of each incidence of the collapse in this traffic. Both the incidence of lightning strikes and the absence of traffic significantly and strongly predict the number of tweets about the conflict (as well as all tweets) from Israel and Palestine, conditional on the severity of attacks on the two sides of the conflict, seasonality, as well as other weather shocks, which could potentially affect conflict events, such as the strength of rain and wind.

We provide two pieces of evidence in support of the exclusion restriction. First, neither the lightning strikes nor the incidences of the absence of traffic correlate with the timing or any observable characteristics of the attacks on either side of the conflict. This suggests that the timing of internet outages is orthogonal to the newsworthiness of the conflict events. Importantly, even though Israel has the ability to turn the internet off in Gaza completely, this does not constitute a threat to our identification strategy for the following reasons. It would bias our results against finding the effects because it only makes sense to shut down the internet when some newsworthy events are taking place. Israel is unlikely to do so because a substantially cheaper way for the authorities to block social media is by jamming the signal in a limited geographical area or staging a Distributed Denial of Service (DDoS) attack on a particular internet resource rather than by pooling the plug of local internet connection, neither of which affect our instrument. Finally, as shown below, our main results are robust to using lightning as the only exogenous source of variation in social-media access in the conflict zone.

Second, we show that, while having a strong and significant negative impact on the Twitter activity of users in Israel and Palestine, internet outages do not have any effect on the news about Israel and Palestine in all major news wires. Furthermore, there is abundant anecdotal evidence that news agencies and foreign correspondents, when they report from the conflict zone, have access to power-surge protection and satellite internet connections making their connection immune to lightning strikes and collapses in local internet traffic.

Overall, we conclude that a dummy indicating the days with internet outages, i.e., local lightning strikes and the absence of visible local internet traffic, is relevant, as it explains the variation in the number of tweets from the conflict zone, and is excludable, as it is extremely unlikely that it correlates with the unobservable component of the newsworthiness of the attacks and with the technology of traditional-news production that does not rely on getting information through social media. (Below, we discuss the validity of our identification assumptions in detail.)

The magnitude of the results is substantial. On average, an internet outage leads to an 18% decrease in the number of tweets from Israel and Palestine about the conflict. Such a decline in tweets about the conflict causes a 6.5-minute decrease in the length of conflict-related news on an average US TV channel per day. (This is equivalent to a 50.7% fall compared to the mean length of news about the conflict zone). It also leads to a 2.5-percentage-point decrease in the probability of prime time coverage (25% of the mean). Provided that the US TV news cover the conflict, the conflict-related stories decrease the intensity of the negative emotions—fear, anger, sadness, and disgust—by 7% of the standard deviation on days when social media is muted by the internet outages in the conflict zone, compared to the days when it is not muted. In addition, the mentions of civilians decrease by 6% and of children and teenagers by 17% of their respective means, when there are outages. Finally, we find that both Palestinian and Israeli civilians affected by the conflict get more coverage on US TV due to the social-media activity in the conflict zone. Yet, on average, in any given time period, the additional TV coverage of conflict due to the absence of internet outages in the conflict zone is devoted to covering Palestinian civilian victims 7 times more than Israeli victims because Palestinian side has an order-of-magnitude larger civilian death tall. This result highlights the democratizing role of social media in conflicts, which gives voice to civilians irrespective of the military outcomes of the conflict or gatekeepers of official conflict-related information.

We do not have data that could allow us to test whether information from social media used by the traditional-media journalists is accurate. False news do circulate widely on social media (e.g., Allcott and Gentzkow, 2017; Vosoughi et al., 2018); and conflict is a topic for which some actors have particularly strong incentives to promote misleading narratives (Patrikarakos, 2017; Singer and Brooking, 2018).[4] Surveys of traditional-media journalists, who rely on social media in their work, show that they are concerned with accuracy of the information available on social media (Cision, 2017, 2020). Thus, whether false information from social media could reach consumers of news by traditional media depends on the standards of fact checking which vary across media outlets. As we consider the main national US TV networks, which have in house fact-checking capabilities, one can be reasonably sure that they can fact-check the social-media information they use as a source, if they want to do so. Furthermore, local associations of citizen journalists often help foreign correspondents to verify information available online.[5]

It is worth noting that despite the fact that the Israeli-Palestinian conflict is very special, there is a reason to believe that our results have some external validity because there is abundant anecdotal evidence of the role of citizen journalists in changing the war narrative in other

[4]One example comes from a Facebook post by the Palestinian Ministry of Interior in the summer of 2014 promoting the campaign 'Be aware' aimed at raising awareness of Palestinian social-media activists. It said (in Arabic): *"[1] Anyone killed or martyred is to be called a civilian from Gaza or Palestine, before we talk about his status in Jihad or his military rank. [2] Do not forget to always add 'innocent civilian' or 'innocent citizen' in your description of those killed in Israeli attacks on Gaza,"* (https://www.facebook.com/moigovps/posts/946767052016152, accessed March 12, 2021).

[5]See, for instance, a story in the *Columbia Journalism Review* about the Local Coordination Committees of Syria, an organization uniting citizen journalists in Syrian conflict, Columbia Journalism Review_the_news/straight_news_from_the_citizen.php (accessed March 21, 2021).

conflicts, such as the Syrian civil war or the war in Ukraine's Donbas region.[6]

Our paper's primary contribution is to the bourgeoning literature on the political effects of social media (see, a recent survey by Zhuravskaya et al., 2020). Much of this literature studies how social media affects citizens or politicians and has not considered the interplay between social and mainsteam media.[7] There are two important exceptions. Cagé et al. (2020b) study how the incentives to invest in investigative journalism changed with the arrival of online media with relatively little legal protection of intellectual property rights. Another recent paper by Cagé et al. (2020a) aims at estimating a causal effect of social media on the extent of coverage by traditional media. They show that online editions of French mainstream media cover stories trending on French Twitter using the population of main-stream French media present online and a large representative sample of French-language tweets. For identification, they rely on the structure of the network of Twitter users and news pressure on French Twitter. This paper does not consider how emotional intensity of traditional-media news or how exactly the content of these news are affected by social media.[8]

Our contribution to this literature is four-fold. First, we focus on news on conflict, which allows us to go beyond documenting a causal effect of social media on the extent of news coverage by traditional media. Our paper is the first to shed light on the impact of social media on the content of traditional news: we document that both the tonality and the focus of traditional news on conflict are affected by social media. Second, we use a novel instrument based on local internet outages, which helps to identify the causal nature of the relationship. Third, in contrast to Cagé et al. (2020a), we use the offline news—the actual TV broadcast—as the main outcome, which could be distinct from the news posted by traditional-media outlets online. Fourth, our results about the content of news strongly suggest that social media affects traditional media reporting not only because it serves as an indicator of the demand for news on a particular topic, but also because traditional journalists use social media as an actual source.

We also contribute to the literature on the role of media in conflicts (see, for instance, Yanagizawa-Drott, 2014; Adena et al., 2015; Durante and Zhuravskaya, 2018; Gagliarducci et al., 2020; Armand et al., 2020; Adena et al., 2020). Our contribution is in documenting that social media helps to level playing field in the information space between the conflict actors, who have very different military and propaganda capabilities.[9]

The rest of the paper is organized as follows. In section 2, we describe data sources and

[6]See, for instance, http://www.redcross.int/EN/mag/magazine2012_2/4-9_extra_1.html (accessed March 21, 2021) as well as numerous examples in Patrikarakos (2017); Singer and Brooking (2018); Higgins (2021).

[7]See, for instance, Allcott and Gentzkow (2017); Enikolopov et al. (2020); Levy (2021); Guriev et al. (forthcoming); Petrova et al. (forthcoming); Müller and Schwarz (forthcoming).

[8]There is also a large body of research in the field of communications (surveyed in Lewis and Molyneux, 2018) that studies how traditional media use social media in production and dissemination of news, using surveys of traditional media outlets (e.g., Lysak et al., 2012; Adornato, 2016; Adornato and Lysak, 2017) or analyzing the content similarity between traditional and social media (e.g., von Nordheim et al., 2018). These papers provide important descriptive evidence, but they are not concerned with identification.

[9]Our paper is also related to fast-growing literature that uses text-as-data techniques to analyze questions relevant for political economy (see Gentzkow et al., 2019, for a survey of methods with several applications).

the main variables used in the analysis. In Section 3, we present our empirical strategy and discuss identification assumptions. Section 4 presents the main results, their robustness, and considers the heterogeneity of the effect across TV networks. In Section 5, we ask which side of the conflict benefits from the effect of social media on traditional-media reporting of the conflict. Section 6 illustrates the results with a case study. Section 7 concludes.

2 Data sources and the main variables

In this section, we describe the construction of all our main variables of interest and their sources. We combine daily data on: the content of US television news; tweets about the conflict from the conflict zone; attacks on both sides of the conflict; internet outages in the conflict zone, and weather in the conflict zone. The time span of the merged data set is between November 24, 2009 and April 18, 2016. Summary statistics for all variables used in the main analysis are presented in Tables A1 to A4 in the Online Appendix.[10]

2.1 Casualties of the Israeli-Palestinian conflict

We proxy for the newsworthy events of the Israeli-Palestinian conflict by casualties on each side. Data come from the NGO Israeli Information Center for Human Rights, *B'Tselem* (http://www.btselem.org/, accessed March 22, 2020). The dataset contains daily information on every fatality in the conflict. They include the information on the perpetrator's side (Israeli or Palestinian) and some basic characteristics of the victims, such as citizenship, gender, age, whether the victim is a civilian or has an official affiliation. We also collected information on the exact hour of the attacks for the period between 2013 to 2016. Panel A of Figure A3 in the Online Appendix presents the number of total casualties on a timeline and provides names of particularly deadly campaigns.

2.2 US TV coverage of the Israeli-Palestinian conflict

To construct our main outcome variables, describing whether and how US TV covers the Israeli-Palestinian conflict, we rely on the US Television News Archive, which is a part of the Internet Archive (https://archive.org/details/tv/, accessed March 12, 2021). We focus on the following US TV networks: ABC, CBS, CNN, FOX, MSNBC, NBC, PBS, and Bloomberg, and of Al Jazeera America, a Qatari network, available in the US. The data are available starting July 2, 2009 for all networks, with the exception of Bloomberg, for which the starting date is December 5, 2013, and Al Jazeera, for which the data are available between August 20, 2013 and April 12, 2016. We web-scraped the full transcripts of all news shows broadcasted by these networks with the following tags defined by the archive: "east jerusalem," "gaza," "gaza city," "gaza strip," "hamas," "hebron," "hezbollah," "israel," "jersualem," "palestine," "palestinians,"

[10]Table A1 summarizes variables of interest across all days. Across US TV networks and days, Table A2 summarizes those variables that are defined for all days and networks. Tables A3 and A4 provide summary statistics across US TV networks and days for the variables that describe the content of conflict-related news; they are defined only for days and networks with at least one conflict-related story.

"westbank." We then used these transcripts to identify stories about the conflict zone and built measures of the extent of conflict-zone coverage, its emotional intensity, and topics. We describe the construction of these variables below.

The extent of conflict-zone coverage.—For each network, we define news stories about the conflict zone as segments of the transcript, in which the (stemmed) keywords for the two sides of the conflict: "Israel" and "Palestin" or "Israel" and "Gaza" are mentioned several times within a segment. To be precise, we first identify all news segments, i.e., contiguous news, in which these keywords are mentioned within a maximum of three minutes from each other.[11] As a baseline, we define a story about the conflict zone as the news segment which mentions the actors in the conflict zone at least five times. The results are robust to using any news segment that mentions "Israel" and "Palestin" or "Israel" and "Gaza" at least once as a news story about the conflict zone (as described in the robustness section below). With the baseline definition, there are 22,749 TV news stories about the conflict zone on US TV news in our data and another 5,180 news stories on Al Jazeera.

To measure the extent of coverage of the conflict zone for each TV network and each day, we construct several variables, based on this definition of a news story about the conflict: a dummy indicating whether a network ran a story about the conflict zone during the prime-time news; the total length of conflict-zone-related news (in minutes); the number of news stories about the conflict. We also count the number of times each network mentioned keywords from the conflict zone. This variable does not depend on the definition of the story about the conflict zone.

On average, there is a 24.6% probability that there is at least one story about the conflict zone on any of the networks. Online Appendix Table A5 summarizes the probability and the length of coverage by TV network. Among the US TV networks, PBS and Fox News cover the stories about the conflict zone the most. The unconditional probability that a story about the conflict zone appears on these networks on an average day is about 40%. In contrast, ABC news run a story about the conflict zone on 10% of days. All US networks cover the conflict less than Al Jazeera America, for which the mean frequency of conflict-zone coverage is 67%. Figure A4 in the Online Appendix illustrates that US coverage of the conflict zone is affected by conflict events: there is a substantially higher probability of coverage on days with fatal casualties compared to days without fatal casualties.

In the robustness section, we establish the robustness of our results on the extent of coverage using an alternative data source, the Vanderbilt Television News Archive (https://tvnews.vanderbilt.edu/, accessed March 12, 2021). It contains only short summaries of only evening TV news for only four TV channels, ABC, CBS, CNN, and NBC.

The emotional intensity of conflict-zone coverage.—To study how US TV covers the conflict, we measure the emotional intensity of conflict-zone-related broadcast for each day and TV network. We rely on the NRC Emotion Lexicon which assigns each English word

[11] In order to make sure that we capture the full news story, we add a margin of one minute before the first keyword and three minutes after the last keyword.

among 6,000 words a score between 0 and 1 for each of the following basic emotions: anger, fear, sadness, disgust, joy, trust, anticipation, and surprise (Mohammad, 2018). The scores are derived from the human rankings of associations between words and emotions. For each conflict-zone-related news story and each emotion, we simply sum the emotion scores of all stemmed words, attributing zero to the words that are not in the Lexicon, divide by the total number of words, and multiply by one hundred. This procedure yields the first-approximation measures of the emotional intensity of each news story. To construct more nuanced measures, we also apply the Contextual Sentiment Analysis methodology developed by Hutto and Gilbert (2014) that takes into account degree modifiers, contrasting sentences, and negations.[12] This methodology yields two measures for each conflict-zone-related news story: positive contextual sentiment and negative contextual sentiment.

We, then, aggregate the indices of emotions and of contextual sentiments to get scores for each day and TV network, taking the maximum across all conflict-zone-related news stories for each network each day (when there was at least one story about the conflict zone). We take the maximum across all news stories per network per day in order to maximize the variation in the resulting measure of emotions. This is because the format of some news segments does not leave any room for emotional expression. We use the scores of emotions for each individual emotion and take means by network and day for all negative, all positive, and all neutral emotions. All these measures are between 0 and 100.

The topics of conflict-zone coverage.—To describe what exactly the US TV news stories talk about when they cover news from Israel and Palestine, we take two alternative approaches. First, we count how many times certain keywords appear in a news segment about the conflict zone, divide it by the total number of words in this news segment, and multiply by 100. To reduce the importance of influential observations, we winsorize each measure at the 99th percentile of its distribution. We search for keywords on topics that range from stories about civilian casualties to the involvement of US foreign policy officials in conflict resolution. The list of topics and of the corresponding keywords for each topic are presented in Online Appendix Table A6. This approach fully rests on our own choice of keywords and topics.

As an alternative, to identify topics covered by news stories about conflict, we employ an automated and unsupervised machine-learning topic-detection algorithm, the Latent Dirichlet Allocation (LDA) model (Blei et al., 2003). As a baseline, we consider 25 topics and set the other hyper-parameters at: 0.1 for the mixture of topics within a news segment and 0.5 for the mixture of topics per word. The results are similar with 50 topics and they are not very sensitive to the choice of other two hyper-parameters, for which we chose the baseline values to minimize perplexity which is equivalent to maximizing the log-likelihood per word in the

[12] In contrast to a naive approach of summing up the emotional scores of each word for different types of emotions, this methodology takes the context in which the words are used into account. Consider, for instance, the following two sentences: "I am very happy" and "I am not happy," both of which have the same length and contain a single word with a non-zero emotional score "happy." The Contextual Sentiment Analysis differentiates between the sign and the intensity of emotions in these sentences, whereas the simple sum of the emotional scores does not.

model.

To describe the content of conflict-zone-related broadcasts further, we identify whether they mention small concrete geographical locations in Israel and in Palestinian Territories.[13] We also collect data on whether the conflict-zone-related news mention social media in general or Twitter, Facebook, YouTube, in particular.

We also build measures of similarity of conflict-zone-related stories shown by different US TV networks on the same day. And we measure how similar are the US TV news stories to Al Jazeera's same-day stories. To compare a US network to Al Jazeera, for each day when both networks have a conflict-related broadcast, we build a vector of zeros and ones in a space where each word is a dimension. We assign the value of zero if a particular word is not used by the other network and 1 if it is used. The similarity between the two networks, then, is defined as the cosine similarity, which is the scalar product of the two vectors divided by the product of their norm. This similarity measure is between 0 and 1. It is equal to 0 if there are no words in common, and 1 if the compared broadcasts use exactly the same set of words. The measure does not depend on the length of the broadcasts. To measure the similarity of a conflict story on a particular US network to conflict stories of all other US networks, we build an average vector for all other networks by taking a share of networks where a particular word was used. Then, as above, we calculate the cosine similarity between the vector for a particular network and the average vector for the other networks.

2.3 Twitting from the conflict zone

We web-scraped all original tweets (without retweets) with stemmed keywords Israel, Palestin, and Gaza from the beginning of Twitter to April 18, 2016. We stoped in April 2016 because Twitter changed the rules precluding us from scraping more data. We scrapped Twitter when it was still feasible to access all tweets containing a given keyword, not going through the API. Altogether, there were 48,286,580 tweets with these keywords. Then, we identified the language of each tweet. 35,427,682 of these tweets, i.e., 73%, are in English, which is not surprising as we collected tweets with keywords in English. English-language tweets were written by 5,494,449 different Twitter accounts. We use self-reported information available on user profile to classify accounts into ordinary people, media, officials, businesses, and organizations.

We also use the self-reported user profiles to establish the geolocation of the accounts by matching the reported location to an entry in the GeoNames dataset (https://www.geonames.org/, accessed March 22, 2021).[14] Using this procedure, we identified the location of accounts for 59% of all English-language tweets with keywords. 14% of them

[13] We use the list of all locations in Israel and Palestinian Territories provided by the GeoNames dataset (https://www.geonames.org/, accessed March 22, 2021) and exclude from this list the following big geographic locations: Bethlehem, East Jerusalem, Israel, Jerusalem, Gaza (strip), Old City, Palestine, Ramallah, Tel-Aviv, and West Bank.

[14] In cases, when the account specified several locations, we matched the user to the location with the largest population.

come from the conflict zone: 1,798,851 tweets from Israel and 1,162,494 tweets from Palestine.

Then, for every tweet among all English-language tweets with keywords, we identify whether it is about the Israeli-Palestinian conflict or not. To do this, we follow a bag-of-words approach and train a Naive-Bayes classifier. To fit the model, we use a set of 5,000 manually labeled tweets, such that 4,000 tweets are used as a training sample and 1,000 tweets as a test sample. 80% of all English-language tweets with keywords from Palestinian accounts are about the conflict, whereas only 47% of English tweets with keywords from Israeli accounts are conflict-related.[15] In some cases, whether a tweet is related to the conflict or not could be ambiguous, so that even humans may not perfectly agree on binary classification. This is why we asked a research assistant to act as an alternative "classifier," i.e., to perform a second independent manual labeling of the training set. Table A7 in the Online Appendix presents various statistics comparing the performance of the algorithm to the performance of the research assistant. We find that the algorithm performs almost as well as a human in classifying tweets.

Panel B of Figure A3 in the Online Appendix presents the number of conflict-related tweets from Israel and Palestine over time. The figure illustrates the fact that tweeting about the conflict intensifies during important conflict events. Figure A5 in the Online Appendix presents the composition of Twitter accounts and conflict-related tweets by the type, language, and location of users.

2.4 Internet outages

For identification, we use two datasets that allow us to measure internet outages in the conflict zone driven by lightning strikes and technical failures.

Lightning strikes.—The data on lightning strikes come from the World Wide Lightning Location Network (WWLLN) dataset.[16] This dataset provides the exact coordinates and time of the cloud-to-ground lightning strikes across the globe. We build a time-series dummy indicator for whether any lightning strike occurred in Israel or the Palestinian Territories, excluding deserts, i.e., areas, where the population density is very low.[17] Over our observation period, thunderstorms occurred on average in 14% of days. Note that there is a large spatial correlation in thunderstorms. As a result, we cannot rely on spatial variation in the lightning strikes and use only overtime variation because the territory of the conflict zone is relatively small. To illustrate this, Panel A of Figure A6 in the Online Appendix presents the map of the locations of each lightning strike on the Israeli and Palestinian territories during a stormy day, November 16, 2014. As shown on the map, when a storm occurs, it can affect a large part of the conflict zone. The map also indicates the areas in and outside deserts. As thunderstorms are highly seasonal—85% of all lightning strikes occur between October and March—in all specifications, we include calendar-month fixed effects. To illustrate the seasonality of the lightning strikes

[15] Among all tweets, 60% are about the conflict.

[16] This dataset is collected by the University of Washington and is available under a license agreement from `http://wwlln.net` (accessed March 12, 2021).

[17] We define deserts as subdistricts with a population density lower than 250 people per square kilometer.

across calendar months Panel B of Figure A6 presents the graph of the number of daily lightning strikes by calendar month.

Internet Outage Detection and Analysis.—To measure internet outages that stem from technical failures, we use the Internet Outage Detection and Analysis (IODA) methodology, developed by computer scientists of the Center for Applied Internet Data Analysis (Dainotti et al., 2011; Padmanabhan et al., 2019). This methodology is based on detecting a sudden drop in internet traffic (called "BGP Prefix count") between a certain geographical area (called "autonomous system") and the rest of the World Wide Web (WWW).[18] Without an internet outage, there is sizable visible traffic at all times because there are always some active IP addresses, many of which are automatic. A sudden decrease in the traffic (a fall in the number of visible BGP prefixes) is a sign of a technical failure leading to an internet outage. We collected time-series data on the traffic between autonomous systems in Israel and Palestine and the WWW. These data come from: https://ioda.caida.org/ (accessed March 12, 2021). They are available starting in 2013. We summed the visible prefixes at date level for all main autonomous systems, i.e., local internet providers: Partner, Bezeq, Cellcom, Paltel, Hadara, Watanyia, Jawwal. We identified the list of the autonomous systems and their corresponding Autonomous Systems Numbers (ASN) using data available at: https://bgpview.io/reports/countries/PS and https://bgpview.io/reports/countries/IL (accessed March 12, 2021). Online appendix Figure A7 presents the time series of the local internet traffic on a timeline and its distribution across days. We define a dummy for the absence of (visible) traffic to be equal to the bottom 10% of the distribution. As presented in Panel B of Figure A7, this corresponds to a natural break in the distribution.

We have verified the general claim of IODA creators (Dainotti et al., 2011; Padmanabhan et al., 2019) that the sudden fall in the internet traffic does not reflect the demand-driven differences in the internet use in application to our context. In Table A8 in the Online Appendix, we show that BGP prefix count is not lower on weekends (compared to weekdays) and at nighttime (compared to daytime), whereas the Twitter activity in the conflict zone is, as one would expect.

The incidents of the absence of (visible) traffic are distinct from power outages because, in any autonomous systems, including those in Israel and Palestine, many active IP addresses are powered by independent generators, and therefore, do not rely on electricity supply. For instance, the collapse of the internet traffic is relatively rare in the Gaza Strip in contrast to power outages, which occur very frequently in Gaza. It is well known that Gazans are accustomed to using power generators.

[18]Autonomous system (AS) is a collection of IP addresses with a predefined routing policy, i.e., how data transit between different nodes of the network. Each AS is typically controlled by one or several Internet Service Providers and it corresponds to a certain geographical area. Different ASs may cover overlapping geographical areas. The BGP protocol is used to communicate between ASs. BGP Prefix is the first part of the IP address, which indicates in which AS the IP is located. Thus, observing the BGP Prefix count allows one to see if a given AS is able to communicate with the rest of the Internet network.

2.5 Additional data

Weather.—We also use daily data on rain, wind, and temperature in the conflict zone. The data come from the Israel Meteorological Service Weather Data.[19] The data are provided hourly at 1×1km-resolution. We aggregate them at the day level weighting by the population density of the grid cells to only account of weather in places where people actually live.[20] The rain data measure precipitation in mm, temperature is expressed in celsius degrees, and wind speed in meters per second.

News Wires.—We use all news wires about the conflict zone issued by three major News agencies: Reuters, Associated Press (AP), Agence France Presse (AFP). We collect these newswires from the Factiva database available under subscription at: https://professional.dowjones.com/factiva/ (accessed May 19, 2020). We look for the same stemmed keywords: Israel, Palestin, and Gaza, and for each retrieved news wire we collect the date and time. These data start on September 1, 2012.

News Pressure.—We use the methodology of Durante and Zhuravskaya (2018) and the Vanderbilt Television News Archive to compute news pressure (Eisensee and Stromberg, 2007) on US TV net of news about the conflict zone. This variable equals to the time devoted to top three non-conflict-related stories daily during prime-time news on ABC, CBS, and NBC and measures the importance of newsworthy events that potentially could crowd out news about the conflict zone on US TV.

3 Empirical strategy

We aim at establishing a causal relationship from social media—and other information available online—to traditional media reporting of conflicts.

3.1 Regression equation

As a proxy for the information available on social media and other online resources about the conflict, we use the daily number of tweets about the conflict from the conflict zone. In particular, we want to causally estimate the following relationship:

$$TV^{US}_{n,d} = \alpha_0 log(Tweets^{CONF}_d) + \alpha_1 log(Deaths^{IL}_d + 1) + \alpha_2 log(Deaths^{PS}_d + 1) + \mathbf{X}'_d \gamma + \delta_n + \varepsilon_{n,d}, \quad (1)$$

where n indexes TV networks, d indexes days. $TV^{US}_{n,d}$ stands for different aspects of US TV news coverage of Israeli-Palestinian conflict: the extent of coverage, the emotional intensity of coverage, the topics, and other measures describing the content of conflict-zone-related news in day d by network n. $Tweets^{CONF}_d$ stands for the daily number of tweets about the conflict from the conflict zone, i.e., Israel and Palestinian Territories. This is our main explanatory variable.

[19] http://www.iacdc.tau.ac.il/what-is-space-weather/, accessed February 7, 2020.

[20] The population density data come from the NASA Socioeconomic Data and Applications Center (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11, accessed May 10, 2021).

It is endogenous and below we describe our instrumentation strategy. Note that the number of daily tweets is above zero for all days in the sample.

$Deaths_d^{IL}$ and $Deaths_d^{PS}$ are the daily numbers of fatal casualties on the Israeli (IL) and Palestinian (PS) side of the conflict, respectively. We add 1 to the number of casualties before taking the log because on 84% of days there are no fatalities.[21] As presented in Panel A of Figure A3, during our observation period, two weeks of the most intense fighting during the Gaza War—shaded on the figure—constitute an important outlier in the number of casualties. These two weeks account for over one-half of all fatal casualties during our observation period. To reduce the weight of these very influential observations in the control for the log casualties, as a baseline, we exclude these two weeks from the sample. To make sure that the results are not driven by this sample restriction, below in the robustness section, we show the robustness of our results to: (i) using the full sample, (ii) winsorizing the number of Israeli and Palestinian casualties at the 99th percentile of their respective distributions and controlling for a dummy indicating days on which the number of casualties was winsorized, (iii) excluding from the sample other episodes of the most intense fighting defined as having at least 15 fatalities in a single day; this restriction excludes additional 23 days (1% of the baseline sample).[22]

δ_n is the TV network fixed effect. $\mathbf{X}_d$ is a vector of additional controls. To control for the seasonality, climate change, and the growth of social media penetration, it includes year, month-of-year, day-of-the-week fixed effects. To control for previous conflict events, we control for the log numbers of Israeli and Palestinian casualties (+1) in the last month, i.e., during the time period between $t - 28$ and $t - 1$. To account for ex-ante probability of US news to cover the Israeli-Palestinian conflict, we control for the non-conflict-related news pressure. We also control for the strength of the rain and wind in the conflict zone, which could affect both the conflict attacks and the instrument's effectiveness in predicting social-media activity (as discussed below). To focus on the Israeli-Palestinian conflict, we also control for a dummy indicating the days when Israel is involved in other armed conflicts, such as the Israel-Lebanon border clashes on August 3, 2010 and on December 15 and 16, 2013 and numerous clashes on the Golan Heights, commonly known as "incidents" on Israel-Syria ceasefire line. $\varepsilon_{n,d}$ denotes the error term. As a baseline, we adjust standard errors for clusters at day level. We also report robustness to various alternative assumptions about the variance-covariance matrix.

3.2 Identification

Equation 1 cannot be estimated with OLS because the social-media activity in the conflict zone, measured by $Tweets_d^{CONF}$, is endogenous to the US TV coverage of the conflict due both to omitted variables and reverse causality. Unobservable newsworthiness of attacks may drive tweeting by Israelis and Palestinians as well as coverage by US television. Other important events may crowd out both the social media posts about the conflict in the conflict zone and

[21] As shown in the robustness section below, our results are completely unaffected if, instead, we use an inverse hyperbolic sine transformation.

[22] There are 50 days with Israeli casualties and 350 days with Palestinian casualties in the baseline sample.

its TV coverage in the US. Third, the content available on US TV may trigger activity in social media in Israel and Palestine.

To address these endogeneity problems, we use two sources of exogenous variation: lightning strikes and technical failures leading to internet outages. First, in the absence of power-surge protection tools, lightning strikes may significantly reduce the user‘s ability to connect to the internet. The reason for this is that electrostatic discharges that occur at the moment of a lightning strike cause power surge that damage internet infrastructure, causing outages.[23]

The frequency of thunderstorms depends on the season, as illustrated in Panel B of Figure A6. To account for this, we control for dummies for each calendar month. Furthermore, the effect of lightning strikes on ICT infrastructure depends on local weather (Schulman and Spring, 2011), thus, we control for the strength of local rain and wind and establish the robustness of the results to controlling for the temperature (in the robustness section), which, unlike the rain and wind, does not affect the strength of the first stage. We also control for the calendar year fixed effects to account—among other potential confounding factors—for the climate change, which accelerated during our observation period.

Second, internet outages take place not only because of physical damage of infrastructure but also due to technical (for instance, programming) failures that lead to a temporary fall in connectivity between a certain geographical area and servers located outside it. As we described above in Section 2.4, we use the methodology developed by computer scientists to detect days when internet users in Israel and Palestine cannot connect to the rest of the World Wide Web.

3.2.1 Instrument's relevance

As the baseline instrument, we use a dummy indicating the incidence of internet outages, which is a union of days with lightning strikes and with the absence of traffic. The dummy for the absence of traffic is defined only for a subset of our observation period, namely, starting in 2013. Year dummies control for whether the absence of traffic is taken into consideration by our measure of internet outages. In the robustness section, we show the results using lightning strikes as the only source of internet outages.

Both the indicator of lightning strikes and the incidents of the absence of internet traffic are strong and significant predictors of social-media activity in the conflict zone, and so is the union of the two that we refer to as the internet outages. Table 1 reports the results of the first stage at a daily level. Panel A uses the internet outage dummy as the instrument; Panels B and C use the dummies for lightning strikes and for the absence of traffic, separately. In all other respects, the three panels use the same specification. The dependent variable in the first two columns is the log of all daily tweets from the conflict zone; and in the last two columns, we

[23]There is a consensus among ICT specialists that lightning strikes damage ICT equipment reducing connectivity (Zeddam and Day, 2014; Martin, 2016). In economic research, this fact was used by Manacorda and Tesei (2020) and Guriev et al. (forthcoming), who predict the variation in the speed of rollout of new mobile ICT technologies with cross-sectional variation in the frequency of lightning strikes. The rationale behind this instrument is that infrastructure investments are costlier in places where equipment is frequently damaged.

consider only conflict-related tweets. Odd columns present results on the full sample and even columns on the subsample of days outside most intense fighting, i.e., with the total number of daily casualties not exceeding 15. The coefficients on the dummies for internet outage and for both of its components are negative and statistically significant. At the bottom of each panel, we report F-statistics for the excluded instrument; it exceeds the conventional threshold for the strong instrument in all cases. On average, the number of daily conflict-related tweets is 18 percent lower on the days with an internet outage. It is 13 percent lower on the days with lightning strikes, and 40 percent lower on the days when there is no visible internet traffic in Israel and Palestine.

Neither source of the internet outages implies a total shut down of the internet in the conflict zone. First, the power-surge-protection infrastructure, when available, significantly reduces the risk of local outages during thunderstorms. Second, users, who have a satellite internet connection, are not affected by the absence of visible internet traffic in Israel and Palestine, as their traffic is channeled through a different autonomous system. Third, far from all thunderstorms are sufficiently strong to generate significant power surges.

In Table A9 in the Online Appendix, we explore which users are more affected by internet outages. We classify all Twitter users in Israel and Palestine into ordinary people, media, officials, businesses, and organizations and regress the share of tweets by ordinary people, by users affiliated with media outlets, and by officials in all conflict-related tweets on the dummies for internet outages and its components. We find that ordinary people is the group of Twitter users that is most affected by the outages. The share of Tweets by ordinary people decreases significantly with lightning strikes and the absence of internet traffic. In Table A10 in the Online Appendix, we show that tweets by Israeli and Palestinian users—both all users and ordinary people only—are equally affected by outages as the share of conflict-related tweets from Israel and the shares of tweets by users to use English only, English and Arabic or English and Hebrew are not significantly related to our measures of internet outages.

To understand better the timing of the response of Twitter users to internet outages, we estimate an event-study specification, in which we regress the log number of conflict-related tweets from Israel and Palestine on the dummies indicating days before and after each internet outage episode. When outages happen in two consecutive days, we define this series as a single outage episode. In this analysis, we only focus on the episodes of internet outages for which we observe at least least seven days without outages around each outage to have a proper definition of lags or leads. There are 84 outage episodes that satisfy these conditions. In addition to all baseline controls, we also include fixed effects for days around each internet outage episode to have a well-defined control group. The estimated coefficients relative to day -4 are presented in Figure 1. Irrespective of whether we consider both sources of internet outages together or separately, we find that there is a significant and substantial drop in the number of tweets on the day of the outage and the tweeting rebounds the day after the outage episode ends.

To illustrate the relevance of the instrument, we consider the tweeting activity of an automated Twitter account, Islamic Prayer Times from Gaza (@IPT_Gaza), which informs

Muslims about the times of prayer.[24] We collected information on all times of Muslim prayers and verified that the internet outages, lightning strikes, and the absence of internet traffic in the Gaza autonomous system significantly predict the times when this bot account was supposed to tweet but did not. The results are presented in Online Appendix Table A11.

3.2.2 Exclusion restriction and the exogeneity of the instrument

Internet outages can serve as a valid instrument for social-media activity in the conflict zone if the assumptions of exogeneity and the exclusion restriction are satisfied. Namely, internet outages are not correlated with factors that affect the traditional-media coverage of the Israeli-Palestinian conflict, other than through their effect on social-media activity in the conflict zone. In particular, internet outages should be unrelated to the newsworthiness of the conflict events, the actions of conflict actors, and the ability of traditional-media reporters to produce news from the conflict zone that does not rely on social media and local internet resources as a source of information. These assumptions cannot be rigorously tested fully, as they concern unobservables. In this section, we discuss why a violation of these assumptions is very unlikely in our case and present supporting evidence.

The most important aspect of the newsworthiness of the conflict attacks is observable, namely, whether there are casualties, how many, and what kind. We start by documenting that neither the internet outages nor their two components are significantly correlated with conflict fatalities. In Table 2, we regress dummies for the internet outage, lightning strikes, and the absence of traffic on the log number of casualties on both sides of the conflict as well as the baseline controls. In Panel A, we consider all fatal casualties. In Panels B, C, and D, we decompose Palestinian casualty counts according to civilian or non-civilian status, gender and age, and the time of the day.[25] We find no significant correlations in any of the considered regressions.

These results provide suggestive evidence to address the following potential concerns. First, conflict attacks could depend on the weather, and lightning strikes are associated with the overall worse weather conditions. Yet, we do not find any correlation between lightning strikes and fatal casualties. Furthermore, in all regressions, we routinely control for the strength of rain and wind, which, arguably, are more important for planning the attacks than the lightning strikes per se, as the military on both sides of the conflict have all the necessary tools for protecting their equipment from power serges generated by lightning strikes.[26]

One could also worry whether the ICT infrastructure could be a target or collateral damage during the attacks and whether conflict actors could disconnect the autonomous systems located in the conflict area from the internet, both of which could potentially result in a decline in visible internet traffic. To the extent that physical damage of the internet infrastructure is correlated with the number of casualties in the conflict, we show that the absence of internet

[24] An example of a typical Tweet of this bot account: "5:07 Now #Fajr Prayer Time for #Gaza #Palestine".

[25] As there are relatively few Israeli casualties, the vast majority of whom are military, there is not enough variation to split Israeli casualties by type.

[26] We also show that our results are robust to controlling for temperature.

traffic is orthogonal to such damage. Not all attacks on infrastructure result in human losses, however. Yet, such attacks, are likely to bias our IV estimates against finding an effect, because attacks are newsworthy, and therefore, the infrastructure damage should be, a priori, associated with higher rather than lower conflict coverage by traditional media.

The next concern is whether conflict actors can disconnect an area from the internet by pulling the plug without incurring any infrastructure damages. As far as the Israeli intelligence capabilities are concerned, it is certainly within the power of the IDF to disconnect Gaza or the West Bank from the internet. If Israel chose to do this, it would also bias the results against finding an effect because shutting down the internet is costly and, therefore, it only makes sense to do it when some important and, therefore, newsworthy events take place, such as a deadly attack, a riot, or a rally.[27] Furthermore, there is a number of alternative strategies at Israel's disposal to disrupt communication in the Palestinian Territories that are substantially less costly than shutting down the entire internet. For example, the military can jam the mobile internet signal in a certain area (e.g., where a riot is taking place) by broadcasting strong radio signals on the same frequency. In addition, hackers on both sides of the conflict can disrupt operations of particular web resources by launching a denial-of-service (DDoS) attack against them. These alternative strategies are not associated with a loss of visible traffic and, therefore, do not affect our instrument.

In the robustness section, we show that our results are robust to using only lightning strikes as the instrument. The potential concerns with deliberate or accidental internet infrastructure damage during the attacks and disconnecting conflict zone from the internet discussed above do not apply to using the lightning strikes as an instrument. Yet, because we are convinced that these concerns are unwarranted and the absence of visible traffic is an important source of variation in social-media activity in the conflict zone, as a baseline, we present results with the instrument that relies on both components of the internet outages.

The exclusion restriction would be violated if US TV correspondents when reporting from the conflict zone, relied on the local internet to transmit their reportages to their news desk. Yet, it is extremely unlikely for any conflict-related reporting, including the US-TV reporting of the Israeli-Palestinian conflict. First, there is ample anecdotal evidence that foreign journalists rely on satellite phones in the conflict zones both for security reasons and in order to be able

[27] During the Israeli Gaza Operation Pillar of Defense in November 2012, which—during our observation period was the second most deadly attack on Gaza (with the 2014 Gaza War being the first)—rumors of a possible internet blackout of Gaza by Israel have proliferated on social media. During that time, Michael Dahan, a professor of Internet and Politics at Sapir College in Israel, in an interview, argued that a possible reason for Israel to disconnect Gaza from the internet would be to prevent citizens from recording and posting information about the presence of Israeli soldiers, highlighting the fact that this would bias our estimates against finding the effect. Dahan argued that this is because the *"internet shutdown would have little effect on Hamas, which relies on Egyptian networks and long-range walkie-talkies to communicate"* (see https://www.huffpost.com/entry/israel-gaza-internet_n_2159407, accessed March 21, 2021). There is no evidence that these rumors have materialized in 2012 or at any other point in time (see, for instance, https://www.eff.org/deeplinks/2012/11/social-media-internet-access-are-latest-weapons-israeli-palestinian-conflict, accessed March 21, 2021). The fact that both fixed and mobile internet worked in Gaza at the peak of the 2014 Gaza War demonstrates that Israel did not shut the internet down even during the most intense fighting. Our data show that the traffic in Gaza autonomous system was stable during the Gaza War (as illustrated in Panel A of Online Appendix Figure A7).

to do their job irrespective of local conditions. For example, an NGO, the Committee to Protect Journalists, states on its website: *"Satellite technology is a critical tool for journalists working in conflict zones where the Internet and other international connections are unreliable or have been shut down by authorities. In 2012, in the Syrian city of Homs—an opposition stronghold bombarded by government forces and effectively cut off by authorities seeking to quash news coverage—international and local journalists used satellite technology to file reports and communicate with news organizations."*[28] A company selling satellite-phone equipment to journalists explains its mission as follows: *"Satellite phones are in fact playing an increasingly important role in news and information flows during times of crisis. Think about how some journalists have had to report 'up to the minute' news from the front lines in places like Iraq... the journalists are able, for example, to speak to their news desk back in their native or working countries, without having to rely on the telephone networks of the war zones..."*[29]

Second, to verify that the technology of news provision by traditional-media reporters does not depend on the local internet, we use the news wires by Agence France-Presse (AFP), Reuters, and Associated Press (AP) news-agency companies, available starting September 1, 2012. We identify all reports about Israel and Palestine using keywords and count how many segments of news wires are devoted to the conflict zone per day in each news agency. We, then, regress the log number of these reports on internet outages and their components, controlling for all baseline controls and news-agency fixed effects. Columns 1 to 3 of Table 3 present the results. We find that the news wire reports about the conflict are not affected by internet outages, lightning strikes, and incidents of the absence of traffic. In columns 4 to 9, we also verify that the number of all tweets from the conflict zone and the number of conflict-related tweets are significantly related to the internet outages and their components on the same sample of days, for which news wire data are available.

Overall, we conclude that internet outages in Israel and Palestine are a valid instrument for the presence of information about the conflict available on social media and other internet media that traditional-media reporters can use as a source. Thus, we instrument the number of conflict-related tweets from the conflict zone, used as a measure of this information, with a dummy for an internet outage in the conflict zone.

4 The effect of social media on traditional-media reporting

4.1 The main results

In this section, we present three sets of results on the effect of social media in Israel and Palestine on TV news coverage of the conflict in the US. We start by documenting the effect on the extent of conflict coverage. Then, we shift our focus to how social media affects the tonality and topics of conflict-related news.

[28]See https://cpj.org/reports/2012/04/armed-conflict/#6, accessed March 22, 2021.

[29]See https://www.verasatglobal.com/en/how-satellite-phones-are-helping-journalists/, accessed March 22, 2021.

4.1.1 The extent of conflict coverage

Figure 2 illustrates the results for the extent of coverage with a reduced-form raw correlation. We summarize alternative measures of the extent of conflict coverage by US TV news (across days and TV networks) separately on the days with and without internet outages. On average, all of the measures of the extent of coverage appear to be substantially lower on the days with internet outages.

A proper instrumental-variable analysis with controls for potential confounds presented in Table 4 yields the same result. In Panel A, we present the estimation of Equation 1. We consider the following measures of the extent of conflict coverage each day in each TV network as outcome variables: a dummy indicating prime-time coverage of the conflict zone, the number of stories broadcasted in one day by each network (including the repetition of the same story over the course of the day), the number of mentions of conflict-related keywords, and the length of time (in minutes) devoted to the coverage of the conflict zone. All regressions have the full set of controls, described in the methodology section and listed in the notes to the table. In the table, we report coefficients on those controls, for which we have a clear prediction. For example, as one should expect, we find that the extent of conflict coverage increases with an increase in the number of Palestinian and Israeli casualties and decreases with an increase in news pressure in the US.

Our focus is on the coefficients on the log number of conflict-related tweets from the conflict zone, instrumented by the internet outage dummy. For all considered outcomes, these coefficients are positive and statistically significant, implying that the extent of coverage increases in the presence of the internet in the conflict zone. Regressions in Columns 1 to 4 are on the full sample. In Column 5, we condition the sample on having at least one story about the conflict zone by the TV network during the day and show that the total length of conflict-zone-related stories increases also conditional on coverage. In Column 6, we restrict the subsample to days with fewer than 15 fatal casualties and find that the conflict coverage is higher when conflict-zone internet is not muted by the outages also outside the episodes of the most intense fighting.

The magnitude of the effect is substantial: an 18-percent decline in the number of conflict-related tweets—the average-size decline driven by an internet outage—causes a 2.5-percentage-point decline in prime-time conflict coverage on US TV (or 25% fall from its mean), a decline in the number of stories per day by 0.35 (46% of its mean), a decline in the mentions of the conflict-zone keywords by 13 keywords (57% of the mean), and a 6.5-minute decline in the length of conflict-related broadcast per day (equivalent to a 51% fall from the mean).[30]

Table B1 in the Online Appendix presents the OLS results for comparison.[31] The IV estimates are about twice as large as the OLS results. At first glance, this could seem surprising

[30]For all regressions, presented in the paper, we report the mean of the dependent variable at the bottom each table.

[31]Section B of the Online Appendix reports OLS results for every IV result presented in the main text, table by table.

because the endogeneity of conflict-related tweets should result in an upward bias in the OLS estimates. However, the IV estimates could be larger due to the following important factors. First, a measurement error from the misclassification of tweets' content and location would bias OLS estimates toward zero. Second, the IV coefficients reflect the effect of the muting of all social-media activity (as well as local online media) that foreign correspondents and other international journalists may use as a source, whereas the OLS specification estimates only the effect of the number of tweets. Third, in presence of heterogeneity of the effect, IV-coefficients estimate the local average treatment effect (LATE) on compliers, i.e., they estimate the effect of information available online from those users who have the ability to make social-media posts only when there are no internet outages. This information comes from users without power-surge protection or satellite internet. Thus, the most likely compliers are the ordinary people witnessing conflict events, i.e., citizen journalists. It is probable that US TV coverage of the conflict is more affected by information posted online by citizen journalists because this is the kind of information that foreign correspondents cannot otherwise access.

In Panel B of Table 4, to our baseline list of covariates, we add the interaction terms between the log number of conflict tweets and the log numbers of Palestinian and Israeli casualties (+1) in order to test whether there is a differential effect of social media depending on the number of fatalities on the two sides of the conflict. This specification has three endogenous variables: the log number of conflict tweets and the two interactions. We instrument them using the dummy for internet outage and its interaction with log numbers of Palestinian and Israeli casualties (+1). The F-stats from the first stage are sufficiently high in the full sample and in the sample excluding days with most intense fighting, i.e., days with at least 15 fatalities. However, when we condition on coverage of the conflict by US TV, the first stage is sufficiently strong only in the subsample of days excluding the most intense fighting. When we condition on coverage, we ask a lot from the data when we want to identify separately three endogenous variables.[32] This is why in Regression 11 (Column 5 of Panel B), in addition to conditioning the sample on coverage, we restrict it to days with less than 15 deaths in the conflict. The specification with interactions yields positive coefficients on all three variables of interest, but their statistical significance varies. The direct effect of the conflict tweets, which estimates the effect of social media on traditional-media reporting on the days when there are zero fatal casualties, is significant for the number of conflict-related keywords and the length of

[32]The most intense fighting defined as having at least 15 casualties occurs in 23 days out of 2,294 days (and 170 day $\times$ network observations out of 16,900, or 1% of the sample). 4 of these days take place during the 2012 Operation Pillar of Defense and the rest during the 2014 Gaza War. During these days, we have practically no variation in the instrument as there is only one day with an outage (a thunderstorm on November 18, 2012) in this subsample. During these days of most intense fighting 94% of day $\times$ network observations had conflict coverage, i.e., almost all networks ran at least one story about the conflict every day. In contrast, outside the time of the most intense fighting, only 24% of observations had conflict coverage. Thus, unfortunately, when we condition on coverage, the period of the most intense fighting has a substantially larger weight in the regression, which makes the first stage weaker. In turn, in the case when we need to predict three endogenous variables at the same time, the first stage becomes too weak. Importantly, all the results that we report for the full sample are robust to restricting the sample to days with less than 15 casualties, as shown in the robustness section below.

the broadcast and not for other outcomes. In all but one specification, the coefficients on the interaction between the log conflict tweets and the log number of Palestinian casualties (+1) are statistically significant, whereas the coefficients on the interactions with the log number of Israeli casualties (+1) are insignificant. Yet, we cannot reject the equality of the magnitude of these coefficients. Thus, these results suggest that social media in the conflict zone has an effect on the extent of conflict coverage by US TV with or without casualties, while we can not detect significant differences between the effects in presence of Palestinian or Israeli casualties.

In sum, traditional media reports more news about the conflict when social media in the conflict zone is not muted by internet outages.

4.1.2 The emotional intensity of conflict coverage

To study how social media affects the emotional intensity of conflict news, we focus on the variation across the TV news stories about the conflict zone. As described in the data section, for each day and TV network, we construct scores of the emotional intensity of conflict-related broadcast based on the use of words associated with certain emotions divided by the total number of words and, alternatively, based on the contextual sentiment that takes into account negations, contrasts, and amplifiers.

We illustrate how the intensity of negative emotions of the conflict-related stories are affected by internet outages in the conflict zone with reduced-form raw data correlations in Figure 3. It presents the means of emotional scores of conflict-related broadcasts across all days and TV networks with at least one story about the conflict zone separately for days with and without internet outage. The figure shows that words with higher negative emotional intensity are used more frequently during US TV news stories about the conflict zone when the internet is not muted by outages in Israel and Palestine.

The results of the 2SLS estimation presented in Table 5 confirm these raw-data correlations. The outcomes in the first four columns of each panel are based on the contextual sentiment analysis and, in the last two columns, the outcomes are the scores based on the use of emotional words. Odd columns present the estimation of the average direct effect of conflict tweets on the full sample (Equation 1) and even columns present the estimation of the interactions between conflict tweets and casualties on a subsample of days with less than 15 casualties. As for this more demanding specification, the first stage is strong enough only excluding the episodes of the most intense fighting, we make this sample restriction in each even column.

Panel A of Table 5 focuses on the negative emotions (Columns 1 to 4) and the use of all emotional words (Columns 5 and 6). In particular, it presents the results for the score of the negative contextual sentiment, the mean of the scores of the negative emotions (anger, fear, disgust, sadness), and the mean of the scores of all emotions (anger, fear, disgust, sadness, joy, trust, anticipation, and surprise). The coefficients on the log number of conflict tweets are positive and statistically significant in both specifications estimating the direct effect of tweets on negative emotions (Columns 1 and 3). Furthermore, as reported in Columns 2 and 4, much of this positive effect is driven by the effect of tweets on those days when there are non-zero Palestinian casualties. In the specification with the interactions, the coefficients on the log conflict tweets in these regressions estimate the effect of Twitter when there are zero casualties, and they are insignificant and substantially smaller than in the respective odd columns, whereas the coefficients on the interaction of log conflict tweets with log(Palestinian casualties +1) are large, positive, and statistically significant. In contrast, the coefficients on the interaction with Israeli casualties are small in magnitude and insignificant for both outcomes measuring negative emotional intensity, suggesting that social media makes the traditional-media broadcast more emotional only in presence of Palestinian victims. A possible explanation for this asymmetry is that the US TV news is generally more emotional in its coverage of the conflict, in presence of Israeli victims irrespective of the information available on social media. This is confirmed by the positive and larger coefficients on the Israeli casualties both at t and in the past month (see Regressions 1 and 3). The direct effects of Palestinian casualties on the negative emotions of US news, on the contrary, are small and insignificant. There could be several possible explanations for why US TV news is more emotional, on average, in presence of Israeli casualties than in presence of Palestinian casualties. This difference could, for instance, be due to better access to information for traditional media in case of Israeli casualties because Israeli authorities assist foreign journalists when they cover stories of Israeli victims or it could be due to a possible bias in the US media in favor of Israel (e.g., Durante and Zhuravskaya, 2018). In Regressions 5 and 6, we show that the result on higher emotional intensity of US news about conflict zone in presence of conflict-zone social media when there are Palestinian casualties is robust to using all emotional words and not only words associated with negative emotions.

As shown in Panel B of Table 5, social media in the conflict zone does not increase the positive emotions of conflict-related news of traditional media. The panel presents the results for the score of the positive contextual sentiment, the mean of scores of positive emotions (joy and trust), and the mean of scores of neutral emotions (anticipation and surprise). There is no effect of social media in the conflict zone on positive emotions in the conflict-related TV broadcast. This is true for the direct of effect of the conflict tweets and for the interactions with casualties on both sides of the conflict (as can be seen from regressions 7 to 10). We find only one significant positive coefficient on the interaction between Palestinian casualties and conflict tweets for the score of neutral emotions, suggesting that social media in the conflict zone increases the use of words associated with anticipation and surprise in conflict-related TV news as well (Regression 12).

The results are very similar when we consider scores of emotions individually for each of the eight basic emotions with two caveats: These is only a direct effect of social media on the use of words associated with disgust, whereas the coefficients of the interactions with casualties are insignificant, as presented in Online Appendix Table A12. This table also shows that direct effect of Israeli casualties at t is significant and positive for all negative emotions, except disgust.[33]

[33] We find also a positive and significant coefficient on the interaction of tweets with Palestinian casualties for

We interpret the magnitude of these effects in two ways. First, one can compare these effects to the standard deviation of the outcome variables. An average-size decline in the number of conflict tweets from the conflict zone as a result of an internet outage (18%) causes increases in the negative emotional sentiment equal to 10% of its standard deviation and in the score of negative emotions equal to 7% of its standard deviation. Second, we can compare these magnitudes to the emotional intensity of different words in the emotions lexicon. On average 20% of all words in a conflict-zone-related newscast have a non-zero emotional intensity, as many words are neutral and a significant number of words are articles and auxiliaries. The estimated effects imply that the average difference in the emotional intensity of words used by US TV news stories about the conflict shown at the time when there is internet outage in the conflict zone compared to the times when there is no internet outage is similar to a difference between "disagreement" and "catastrophe," or the difference between "prejudice" and "assault," or between "storm" and "bloodshed."[34]

4.1.3 The topics

In this section, we study how the content of conflict-related news stories is affected by social media in the conflict zone. We start with the analysis of keywords on a number of specific topics. Table 6 presents the results. First, we find that mentions of civilians and people per 100 words of the conflict-zone-related TV news (Regressions 1 and 2) and mentions of words that refer to children, babies, and teenagers per 100 words of the conflict-related TV news (Regressions 3 and 4) are higher when social media is not muted by internet outages in the conflict zone. The same is true about the words related to terrorism (Regressions 7 and 8). These effects do not depend on the number of casualties. Mentions of civilian casualties are also more frequent with conflict-zone social media unmuted, but only when Palestinians die in the conflict (Regressions 5 and 6). We also find that Benjamin Netanyahu and Mahmoud Abbas, as well as Israeli and Palestinian authorities, are mentioned more frequently (Regressions 11 and 12) with social media, whereas Hamas is mentioned more in presence of Palestinian victims (Regressions 9 and 10). As the outcome variables are expressed as a share of the total length of the conflict news, a natural question is which topics are less discussed by US TV news about the conflict in presence of conflict-zone social media. We find that US foreign policy officials (i.e., the mentions of the two secretaries of state who were in office during our observation period) and words related to elections are mentioned less frequently in the US TV news about

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the use of words associated with joy. However, as the respective coefficient for the positive contextual sentiment is small and insignificant, we attribute this fact to the absence of correction for negations in simple counts of the emotional scores.

[34]The OLS results corresponding to the 2SLS results from Table 5 are presented in the Online Appendix Table B2. Comparison of the IV and OLS results on the direct effect of social media yields that: (1) as one would expect, there is a strong upward bias in OLS estimates for the positive and neutral emotions; and (2) for the negative emotions, the OLS estimates of the direct effect of tweets are somewhat smaller in magnitude than the IV estimates, which, as in the case of the extent of coverage, could be due to the heterogeneity of the effects. We also find that the OLS estimates of the effect of social media on negative emotions in the presence of Israeli casualties have an upward bias and of the effect of social media in presence of Palestinian casualties have a downward bias.

the Israeli-Palestinian conflict with unmuted conflict-zone social media (Regressions 13-16). The results imply that an average-size internet outage in a conflict zone leads to a decline in the mentions of Israeli and Palestinian civilians and people by 0.02 in 100 words by US news, equivalent to a 6% decline from the mean and a 10% decline of the standard deviation. The mentions of children and teenagers decline by 0.005 in 100 words, which is equal to 17% of its mean and 9% of its standard deviation. Figure 4 illustrates the reduced form behind these relationships with several raw-data correlations.

We also test whether US TV news programs explicitly refer to social media more in their news stories about the conflict during days when social media is not muted in the conflict zone by internet outages. The results are reported in Panel C of Table 6. As a dependent variable, we use a dummy for whether there is a mention of Twitter, Facebook, YouTube, or "Social media." We find a significant positive effect on Twitter and Facebook—the two platforms referenced by the US TV conflict stories the most—with mentions of Twitter particularly affected in presence of Palestinian casualties. We find no significant effect for YouTube and a marginally significant positive effect on the mentions of social media in presence of Palestinian casualties. An 18-percent decline in the number of tweets about the conflict from the conflict zone caused by an average-size internet outage leads to a 2 percentage-point decline in references to Twitter and a 3 percentage-point decline in references to Facebook.[35]

As an alternative approach to identifying the concrete topics of the conflict-related US TV broadcast, we use the machine-learning (LDA) algorithm to identify 25 topics. Table 7 presents the results using seven out of 25 topics that have at least one statistically significant coefficient on either the log conflict tweets or its interaction with Palestinian or Israeli casualties. These topics can be broadly classified as being about terrorism, Netanyahu, elections, settlements, US secretary of state, Obama, and attacks. The table also presents results for another 3 topics about the attacks, which we cannot distinguish—by browsing through the most frequently used words—from the topic on the attacks that did generate significant results. Table A13 in the Online Appendix presents the results for each of the other topic (out of 25), for completeness.[36] As reported in Table 7, we find that topics related to terrorism and Netanyahu are significantly more likely and topics related to elections, settlements, and US foreign policy officials are less likely with social media presence in the conflict zone (see rows 1 to 5). Topics related to Barack Obama are also less likely, but only in presence of Palestinian casualties (row 6). The algorithm identified four topics related to attacks, for one of which, there is a significant positive effect of conflict tweets interacted with Palestinian casualties and a negative significant effect of conflict

[35] One should interpret these magnitudes with caution, as on TV news the reference to the source may not appear in the transcript, which we analyze, but could be given on the image (see, for instance, Figures A1 and A2 in the Online Appendix.) Online Appendix Table B3 presents OLS results corresponding to IV results of Table 6.

[36] Tables 7 and A13 are transposed compared to the usual table layout in order to leave space for the examples of keywords used frequently by topic identified by the algorithm. Each row presents the results of two regressions: (1) specification with only the direct effect of conflict tweets and (2) specification with the direct effect and the interactions with casualties. The last column reports the mean of the dependent variable, i.e., the mean probability that conflict-related US TV news focuses on each topic.

tweets interacted with Israeli casualties (row 7). In row 11, we test for the effect on all topics related to the attacks together and find that US TV is more likely to talk about the attacks in presence of Palestinian casualties when there is access to social media in the conflict zone. As "people" or "civilians" are among the most frequently used keywords in all LDA topics related to attacks, we interpret these results as being broadly consistent with our analysis of the content of conflict-related news using pre-selected keywords. An 18-percent decline in the number of conflict tweets leads to a 1.4 percentage point decrease in the probability of any US TV news about the conflict zone to be about the attacks, which is a 12% decline from the mean probability.

In Table 8, we address the question of whether US TV news stories about the conflict contain more details about the events on the ground when social media is not muted by outages in the conflict zone. First, we consider the mentions of names of heavy ammunitions in the total number of words and find that it is significantly higher with social media in the conflict zone when there are Palestinian casualties (Regressions 1 and 2). Second, we identify all mentions of concrete small geographic locations in Israel and Palestine and use a dummy for mentions of those locations as the dependent variables. For the Israeli geographic locations, we do not find a significant effect of conflict-zone social media, even though when Israelis die, US TV news do mention small Israeli places more (as reflected in the significant direct effect of log Israeli casualties +1). Social media in the conflict zone, in contrast, does increase the mentions of the Palestinian geographic locations when there are Palestinian deaths. This evidence is consistent with the view that when there are Israeli casualties, authorities provide foreign journalists with full information about them.

Finally, we examine the similarity among conflict-related news stories broadcasted by different TV networks on the same day. Panel B of Table 8 presents the results. We restrict the sample in this analysis to days when at least two of the considered networks ran a story about the conflict zone. In regressions 7 and 8, as dependent variable, we use similarity between conflict-related broadcast by a US TV network to all other stories about the conflict on US TV on the same day, we find that social media in the conflict zone makes conflict news stories by different US TV networks more similar to each other. In regressions 9 and 10, we show that conflict-related stories run by US TV networks become more similar to those by Al Jazeera America with conflict-zone social media not muted by internet outages. In regressions 11 and 12, we show that this effect is stronger and more precise when we consider the three US networks that cover the conflict most: CNN, FOX, and PBS.[37]

Overall, the analyses of the content of US TV news about the Israeli-Palestinian conflict suggest that the focus of these news shifts from topics like the foreign US policy with regard to the conflict toward describing the conflict events on the ground and the suffering of civilians casualties, particularly, when there are Palestinian casualties.

[37]Note that we do not need to restrict the sample to below 15 casualties in the regressions that consider the similarity of US networks to Al Jazeera even in specification with interactions because the first stage works well even without this restriction for the time period when Al Jazeera data are available. Online Appendix Table B5 presents OLS results corresponding to IV results of Table 8.

4.2 Robustness

Section C of the Online Appendix presents results of a battery of robustness checks. In particular, we show that the results are robust to (i) using lightning strike only as instrument, (ii) defining conflict tweets with a more conservative measure or considering all tweets instead of conflict tweets, (iii) defining any TV news story that mentions "Israel" and "Palestin" or "Israel" and "Gaza" even once as a story about the conflict zone, (iv) controlling for temperature in the conflict zone, (v) applying the inverse hyperbolic sine transformation to the number of casualties instead of using $log(x + 1)$, (vi) enlarging the sample to include the thirteen days of the most intense fighting during the 2014 Gaza War with and without winsorizing the number of casualties, (vi) excluding the days with less than fifteen deaths, and (vii) clustering the standard errors to allow for serial correlation over a moving time window of $+/-$ one day or $+/-$ three days around day t. We also show that the results are robust to using the Vanderbilt Television News Archive as an alternative data source on the extent of conflict coverage.

4.3 Heterogeneity across TV networks

To understand whether the results differ depending on the ideological leaning of the TV network, we use the ranking of the ideology of viewers of different networks provided by PEW Research Center (presented in Online Appendix Figure A8). We run regressions separately by network for FOX, NBC, CNN, MSNBC, PBC, and group ABC, CBS, and Bloomberg together, as they have very similar ideological leaning. To understand how the results depend on the position of the TV network with regard to the two sides of the conflict, we also report the results for Al Jazeera America as a benchmark.

Figure 5 summarizes the results by presenting the standardized coefficients on the log number of tweets from the 2SLS regressions by network for three outcomes: the length of the daily conflict-related news, the score of the negative contextual sentiment of the conflict-related news, and the use of words associated with civilians, people, children, babies, and teenagers in the conflict-related news divided by the total number of words in these news. We sort the US networks from the most conservative to the most liberal. For each regression, we also report the F-statistic from the first stage. F-statistics are sufficiently high not to worry about the weak instrument problem in regressions for the extent of coverage, but they are too low in the regressions that rely on variation only between days with conflict-related news within a single network. In order to address this problem, in these regressions, instead of conventional confidence intervals, we report Anderson-Rubin confidence sets with correction for weak instrument problem (Anderson and Rubin, 1949; Mikusheva and Poi, 2006).[38]

We find no heterogeneity across networks of the effect of social media in the conflict zone on the extent of conflict coverage. As far as the emotional content of conflict-related news is concerned, there is also little heterogeneity across US networks with a notable exception: there

[38] In these regressions for ABC, CBS, and Bloomberg, the first stage is particularly weak, which makes the Anderson-Rubin confidence sets too large for any meaningful inference.

is a precisely-estimated zero effect for PBS and a relatively small (and insignificant) effect for Fox News. Interestingly, these are the outlets with the most liberal and the most conservative slant among the considered US networks. We also find a small and insignificant effect for Al Jazeera, which could be explained by the fact that Al Jazeera's news stories about the conflict, on average, are much more emotional than those of any of the US TV networks suggesting that there is no room for making them even more emotional. (Figure A9 in the Online Appendix presents the mean outcomes by TV network.) There is some heterogeneity of the effect by TV network for the mentions of civilians in the conflict-related broadcast, but this heterogeneity is not related to the ideological leaning of the networks. We find the largest effects in FOX—which is the most conservative—and CNN and MSNBC—which are among the more liberal networks—and precisely-estimated zero effect for NBS (rather conservative-leaning) and PBS (the most liberal).[39]

Overall, the main effects are not driven by a particular TV network and do not vary systematically with the ideological leaning of the networks.

5 Implications for the two sides of the conflict

In *War in 140 Characters: How Social Media is Reshaping Conflict in the Twenty-First Century*, David Patrikarakos argues that social media helps to level the playing field in conflicts by moving the power of narrative away from gatekeepers of information in the war zone to ordinary people (Patrikarakos, 2017, p. 21, p. 26). Patrikarakos asserts that in the Israeli-Palestinian conflict such *"democratization of the wartime narrative [...] benefitted only one side: the Palestinians"* (p. 38). He explains that before social media, the IDF was able to control the narrative *"by controlling journalists' access to war zones, or even refusing to accredit certain journalists [...] The Palestinians, conversely, could offer little by way of a counternarrative. The advent of new media has irrevocably altered this"* (p. 21).

The results presented above are broadly consistent with Patrikarakos's argument. To test it further, we combine our analyses of the extent and the content of conflict coverage. On the sample of days excluding the most intense fighting (i.e., with total deaths below 15), we regress the dummy for mentioning Palestinian or Israeli civilian casualties in a particular network on a given day on the log number of tweets and its interactions with the numbers of Palestinian and Israeli casualties. (We use the number rather than the logarithm to be able to quantify the effects per casualty.)

Table 9 reports the results. In Column 1, we verify that the likelihood that US TV runs a news story covering civilian casualties increases with every Palestinian and every Israeli death. The point estimate on the Israeli deaths is about 75% higher than on Palestinian deaths, but the difference between them is not statistically significant.[40] In Column 2, we show that, on average,

[39] We hand-collected information on whether the TV networks have their own correspondent based in Israel. This variable has no time dimension and only varies across networks. It does not have any predictive power to explain the heterogeneity across networks.

[40] As mentioned above, this could be due to differential access of foreign correspondents to information when

there is no significant difference in the likelihood of US TV coverage of civilian casualties in the conflict with and without social media in the conflict zone if one does not differentiate between days with and without casualties. Column 3 demonstrates that social media in the conflict zone increases the likelihood of a story about civilian casualties when there are casualties on both sides of the conflict. The coefficients on the interactions of conflict tweets with the number of Israeli and Palestinian deaths are positive, significant, and not (statistically) different from each other. Their magnitude implies that information about the conflict in the conflict zone posted on social media in the absence of internet outage increases the probability that an average US TV news program mentions civilian casualties by 0.8 percentage points with each additional Israeli victim and by 0.6 percentage points with each additional Palestinian victim (the mean probability across all days outside the most intense flighting is 2.9%). Altogether, there are about 9.5 times more casualties on the Palestinian side than on the Israeli side of the conflict. This implies that, on average, in any given time period, additional TV coverage of the conflict—due to the absence of internet blackouts—is devoted to covering Palestinian victims 7 times more than Israeli victims.

These results suggest that social media in the conflict zone moves traditional-media reporting of conflicts to portraying the suffering of civilians on both sides of the conflict, but it helps the narrative of the side that suffers a higher civilian death toll.

6 A case study: 16-year-old Palestinian citizen-journalist

In the summer of 2014, Farah Baker, a 16-year-old Palestinian girl became an international celebrity (Reading, 2016; Patrikarakos, 2017). International media and news agencies all across the world, including Reuters, CNN, Fox News, NBC, Al Jazeera, RT, The Daily Telegraph, The New York Post, and International Business Times, ran stories based on the content of her english-language Twitter account, where she chronicled what she saw and felt during the Israeli bombing raids on her town during the Gaza War. Patrikarakos writes: *"The majority of articles [by traditional-media outlets] were based on her tweets and the narrative around them. In effect, they treated her Twitter feed like a newswire service; a tweet became comparable to an associate press bulletin"* (p. 34). *Many of her tweets were simple descriptions or videos of what she saw and heard. "This is the car which was bombed at my house door #Gaza #GazaUnderAttack," she tweeted on July 26 with accompanying photo of the destroyed vehicle."... But it was the detailing of her emotions—her fear for her safety and for that of her family, especially her little sister, Lamar—that was by far the most powerful and popular element of her output"* (p. 27). We provide examples of her tweets as quoted by CNN in Online Appendix Figure A1.[41] Many of Farah's tweets were retweeted thousands of times, including by journalists and

there are Israeli vs. Palestinian casualties, a fact that a Palestinian casualty constitutes smaller news simply because they are many more of them or a possible US audience's allegiance to the Israeli side of the conflict.

[41] Note that not only Farah's pictures and videos, but also her text messages were used as a source by US TV news. In addition, print media also ran stories based on Farah's tweets. This suggests that our results are not specific TV news which—unlike print media—require a visual.

opinion makers with many followers amplifying her message. *"Tweets begat retweets, which begat greater audiences, which begat news coverage, which begat demonstrations, which begat yet more news coverage, most of it pro-Gaza" (p. 35)* In an interview Farah told Patrikarakos: *"[with Twitter] more people ... can see what you write, and crucially, journalists use it as a source. People on the ground tweeting photos and descriptions of events during wartime have become invaluable—especially as they often tweet or post from areas too dangerous for journalists to go... It allows the victims of war to gain a voice and the world to view—with greater detail than ever before—just what exactly is happening inside zones of conflict"* (p. 25).

This is the rationale behind the "B'Tselem Camera Project." Since 2007, the NGO distributes video cameras among Palestinians in the West Bank and teaches them how to become citizen journalists and document human rights abuses.[42] Some of the videos shot by the project participants have gained considerable attention on social media, as well as domestic and international media.

7 Conclusions

Social media has changed reporting of conflicts by traditional media. We analyze a causal impact of social-media posts in Israel and Palestine on the news about the Israeli-Palestinian conflict by main national US TV networks. We rely on the exogenous variation in the social media posts about the Israeli-Palestinian conflict driven by internet outages in the conflict zone. While having a strong and significant negative impact on social-media activity in Israel and Palestine—measured by the number of tweets about the conflict—these internet outages do not affect major news wires about the conflict zone. We show that comparable conflict events get significantly higher TV coverage in the US if they happen during times when social media is not muted by internet outages in the conflict zone. Using text analyses of transcripts of US TV news programs, we document that the emotional intensity and the content of the conflict coverage by US TV are affected by social media. On average, social media makes traditional-media reporting of the conflict more emotional, particularly in presence of Palestinian casualties. When social media is not muted in Israel and Palestine, the US TV news about the Israeli-Palestinian conflict provide more details about the events on the ground and focus more on stories about civilians' suffering and less on the role of US foreign policy and elections.

Our results suggest that social media moves traditional-media reporting of conflict from portraying the point of view of war gatekeepers toward portraying the point of view of the ordinary people, who suffer as a result of the conflict on all its sides. This highlights the democratizing role of social media. Eventually, this helps to further the narrative of the side of the conflict that suffers a higher civilian death toll.

[42] See, for instance, https://www.btselem.org/video-channel/camera-project, accessed March 21, 2021.

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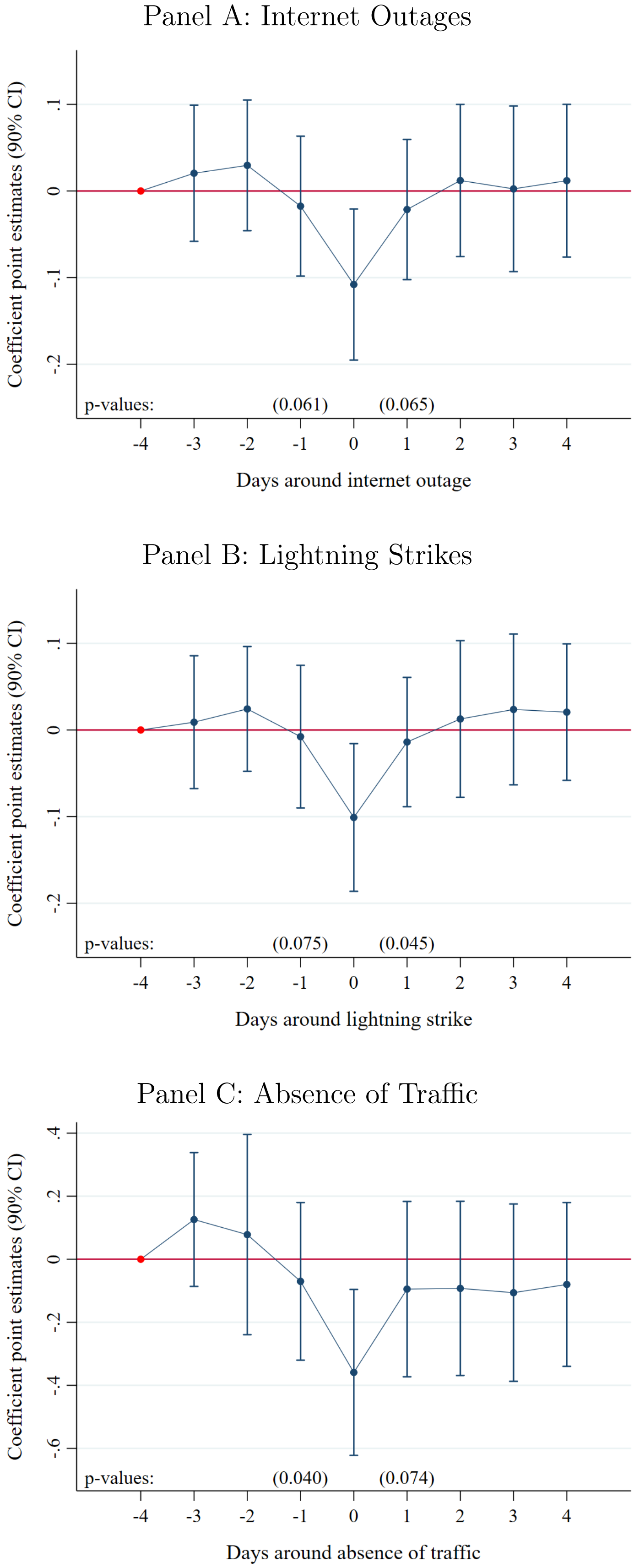
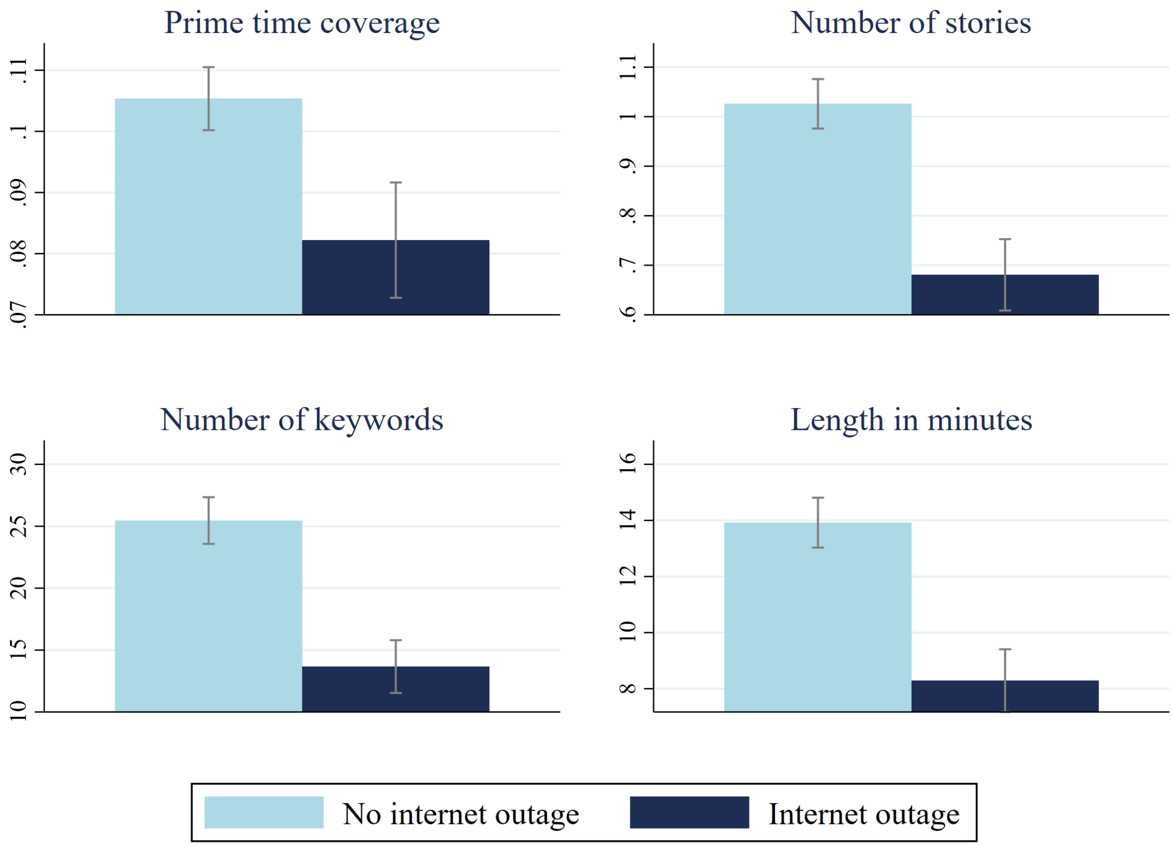
Figure 1: Illustration of the first stage with an event-study: tweets and internet outage



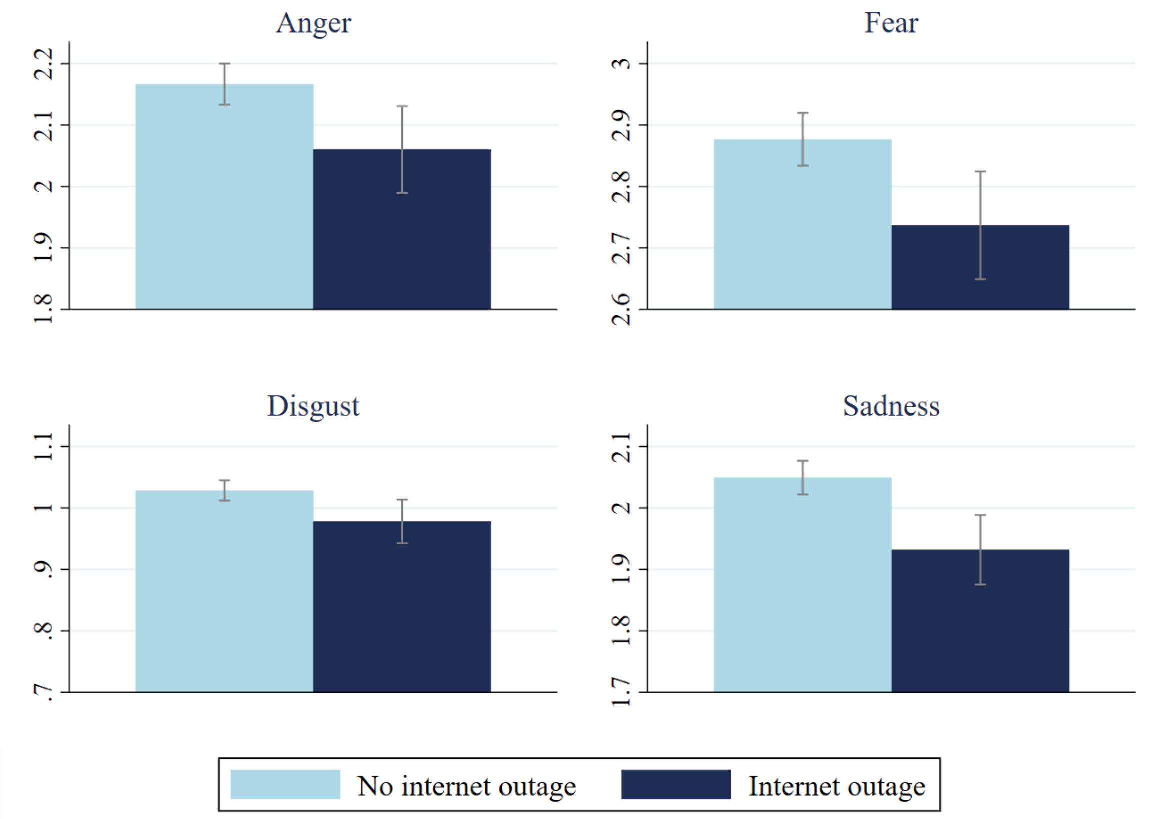
Note: The figure presents the results of an event-study estimation, in which log number of conflict-related tweets from the conflict zone is regressed on the lags and leads of internet outages. Below the coefficients on the dummies for the day before and the day after the outage, we present the p-values from the Wald test of the equality of these coefficients with the coefficient on the dummy for day zero.

Figure 2: Internet outages and the extent of conflict coverage, reduced form



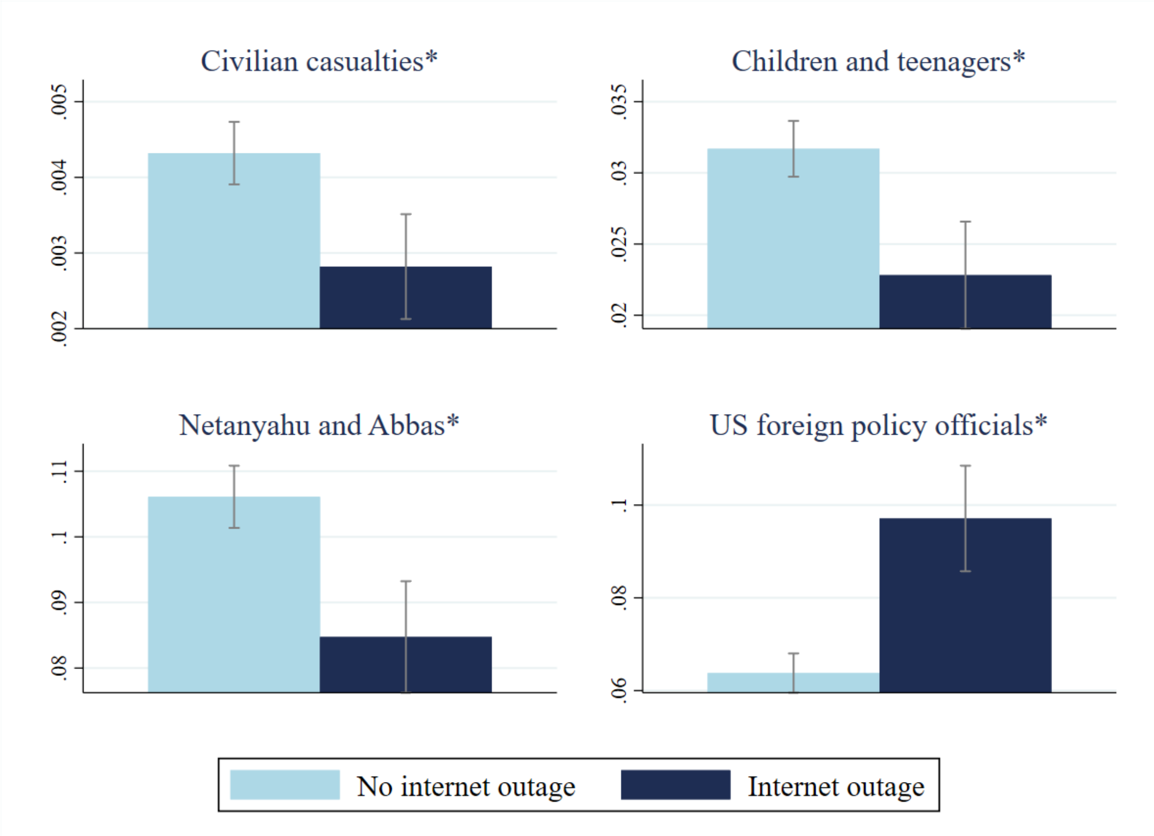
Note: The figure presents an illustration of the reduced-form relationship between the extent of conflict coverage by the US TV and internet outages in the conflict zone. The graphs summarize various measures of the extent of coverage across days and TV networks separately for the days with and without internet outage. The unit of observation is a day × TV network. Sample: all days and TV networks. Prime time coverage is a dummy that equals to one if the conflict is covered on prime time in a given network over a given day. The number of stories and the number of keywords measures the number of TV news stories on the conflict and the number of conflict-related keywords ("israel*", "palestin*", and "gaza*") in a given network over a given day, respectively. Length in minutes measures the total number of minutes devoted to the conflict in a given network over a given day.

Figure 3: Internet outages and emotional intensity of conflict coverage



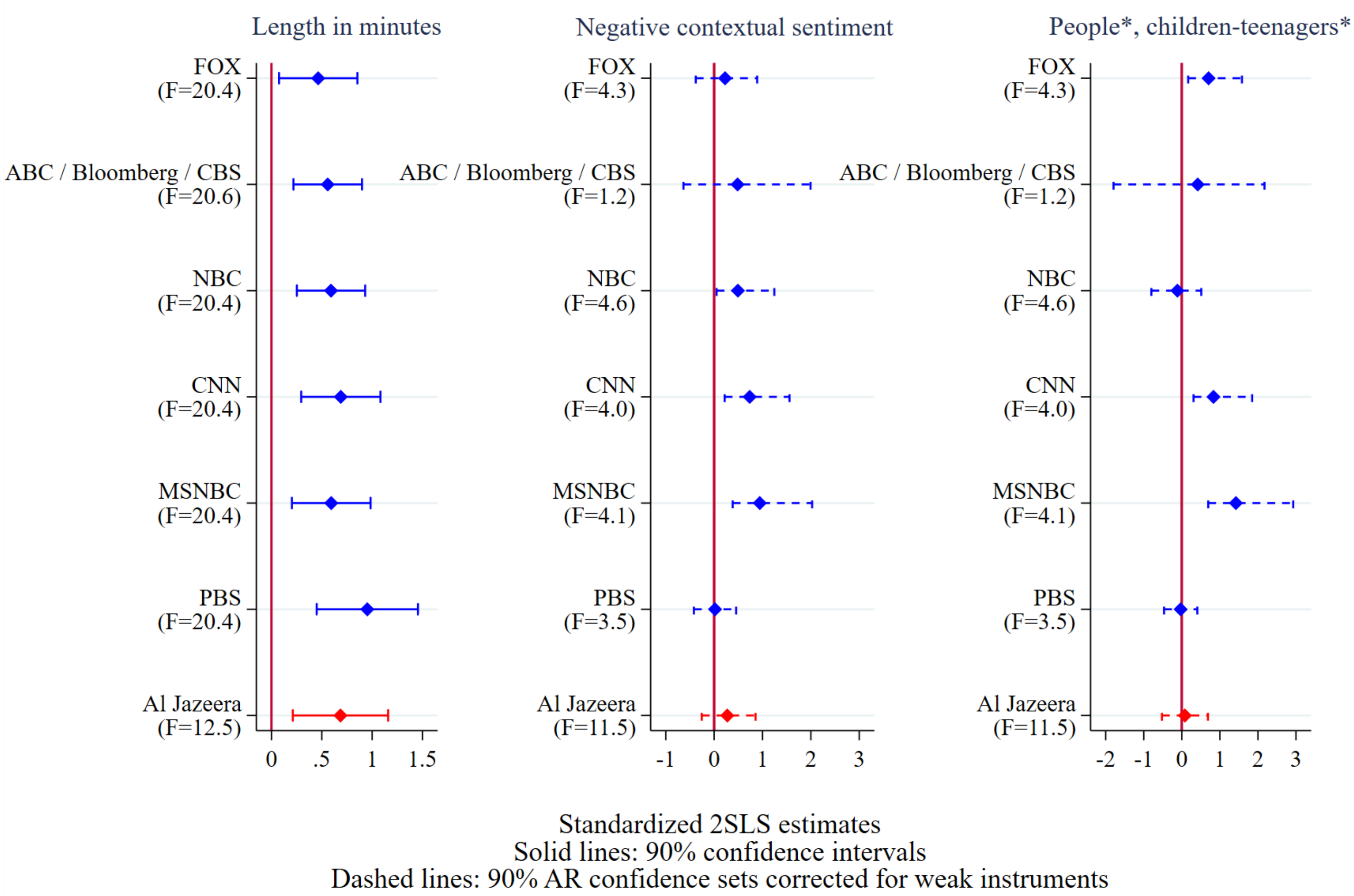
Note: The figure presents an illustration of the reduced-form relationship between emotional intensity of coverage of the conflict by US TV news and internet outages in the conflict zone. The graphs summarize the emotions scores of conflict-zone-related broadcast across days and TV networks separately for the days with and without internet outage. The unit of observation is a day $\times$ TV network. Sample: all days and TV networks with at least one story about the conflict zone. We use measures based on the use of emotional words divided by the total number of words.

Figure 4: Internet outages and keywords mentioned by stories on conflict



Note: The figure presents an illustration of the reduced-form relationship between emotional intensity of coverage of the conflict by US TV news and internet outages in the conflict zone. The graphs summarize the emotions scores of conflict-zone-related broadcast across days and TV networks separately for the days with and without internet outage. The unit of observation is a day $\times$ TV network. Sample: all days and TV networks with at least one story about the conflict zone. We use measures based on the use of emotional words divided by the total number of words.

Figure 5: Heterogeneity across TV networks



Note: The figure presents the estimated standardized coefficients of log conflict tweets from the 2SLS estimation of Equation 1 by TV network. We consider three outcomes: the length of TV coverage in a given day; the negative contextual sentiment for the days with conflict coverage; and mentions of people, civilians, children, babies, and teenagers divided by the total number of words in conflict coverage. For the latter two outcomes, we report Anderson-Rubin confidence sets with correction for weak instrument, as the first stage is not strong enough. In parentheses, we report F-statistics from the first stage for each regression.

Table 1: The first stage: Tweets and internet outages in the conflict zone

Dependent variable, all panels:	Log(All tweets)		Log(Conflict tweets)	
Sample days, all panels:	All	Deaths<15	All	Deaths<15
Panel A: Internet Outages	(1)	(2)	(3)	(4)
Internet outage	–0.164***	–0.159***	–0.168***	–0.163***
	(0.039)	(0.039)	(0.037)	(0.037)
Log(Israeli deaths+1)	0.127***	0.122**	0.164**	0.159*
	(0.048)	(0.055)	(0.071)	(0.082)
Log(Palestinian deaths+1)	0.206***	0.137***	0.298***	0.219***
	(0.019)	(0.023)	(0.024)	(0.031)
Log(Israeli deaths+1), t-28 to t-1	0.039***	0.054***	0.058***	0.075***
	(0.013)	(0.013)	(0.015)	(0.016)
Log(Palestinian deaths+1), t-28 to t-1	0.069***	0.062***	0.101***	0.092***
	(0.008)	(0.008)	(0.009)	(0.010)
News pressure	–0.201***	–0.171***	–0.291***	–0.256***
	(0.057)	(0.056)	(0.069)	(0.068)
Other conflict involving Israel	0.038	0.034	0.044	0.037
	(0.033)	(0.032)	(0.046)	(0.045)
Share of population with rain	0.118*	0.109*	0.143**	0.133**
	(0.062)	(0.062)	(0.063)	(0.063)
Mean wind speed	0.502***	0.507***	0.478**	0.487***
	(0.168)	(0.169)	(0.188)	(0.189)
Observations	2294	2271	2294	2271
Controls: Year-, MoY-, DoW- FEs	✓	✓	✓	✓
Mean dep. var.	7.25	7.23	6.32	6.30
F-stat, *Internet Outage*	17.69	16.60	20.44	19.43
Panel B: Lightning Strikes	(5)	(6)	(7)	(8)
Lightning strike	–0.114***	–0.110***	–0.123***	–0.119***
	(0.032)	(0.032)	(0.036)	(0.035)
Observations	2294	2271	2294	2271
Controls: same as in Panel A	✓	✓	✓	✓
Mean dep. var.	7.25	7.23	6.32	6.30
F-stat, *Lightning strike*	12.78	12.20	11.68	11.28
Panel C: Absence of Traffic	(9)	(10)	(11)	(12)
Absence of traffic	–0.347***	–0.331***	–0.360***	–0.341***
	(0.088)	(0.089)	(0.078)	(0.078)
Observations	1174	1155	1174	1155
Controls: same as in Panel A	✓	✓	✓	✓
Mean dep. var.	7.45	7.43	6.58	6.54
F-stat, *Absence of traffic*	15.40	14.00	21.46	19.25

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The unit of observation is a day. All variables without subscripts are measured at day t. "Log(Israeli deaths+1), t-28 to t-1" and "Log(Palestinian deaths+1), t-28 to t-1" stand for the total number of casualties on each respective of the conflict during 28 days prior to day t. "Year-, MoY-, DoW- FEs" denotes fixed effects for each calendar year, each month of the year, and each day of the week. The set of controls is the same in all specifications and all Panels, and is explicitly shown in Panel A. All Panels have the same dependent variables.

Table 2: Exclusion restriction I: Internet outages and attacks

Dependent variable, all panels:	Internet outage		Lightning strike		Absence of traffic	
Sample days, all panels:	All	Deaths<15	All	Deaths<15	All	Deaths<15
Panel A: All Israeli and Palestinian deaths	(1)	(2)	(3)	(4)	(5)	(6)
Log(Palestinian deaths+1)	–0.003	0.019	0.003	0.018	–0.020	0.002
	(0.014)	(0.017)	(0.012)	(0.014)	(0.014)	(0.020)
Log(Israeli deaths+1)	–0.038	–0.026	–0.032	–0.014	0.013	0.004
	(0.043)	(0.049)	(0.038)	(0.042)	(0.026)	(0.032)
Observations	2294	2271	2294	2271	1174	1155
Mean dep. var.	0.19	0.19	0.15	0.15	0.10	0.10
Panel B: Civilian and non-civilian deaths	(7)	(8)	(9)	(10)	(11)	(12)
Log(Palestinian civilian deaths+1)	–0.012	0.003	–0.002	0.006	–0.006	0.004
	(0.022)	(0.025)	(0.017)	(0.019)	(0.022)	(0.024)
Log(Palestinian non-civilian deaths+1)	–0.004	0.026	–0.004	0.018	–0.037	–0.010
	(0.022)	(0.025)	(0.020)	(0.023)	(0.025)	(0.032)
Log(Israeli deaths+1)	–0.032	–0.022	–0.027	–0.011	0.014	0.004
	(0.043)	(0.049)	(0.038)	(0.042)	(0.027)	(0.033)
Observations	2294	2271	2294	2271	1174	1155
Mean dep. var.	0.19	0.19	0.15	0.15	0.10	0.10
Panel C: Female, male, and child deaths	(13)	(14)	(15)	(16)	(17)	(18)
Log(Palestinian female deaths+1)	–0.016	0.028	–0.038	–0.074	0.054	0.162
	(0.078)	(0.111)	(0.058)	(0.060)	(0.075)	(0.104)
Log(Palestinian male deaths+1)	–0.007	0.003	0.000	0.009	–0.024	–0.014
	(0.018)	(0.019)	(0.016)	(0.016)	(0.019)	(0.020)
Log(Palestinian child deaths+1)	–0.003	0.064	0.016	0.063	–0.051	–0.015
	(0.058)	(0.068)	(0.046)	(0.053)	(0.057)	(0.075)
Log(Israeli deaths+1)	–0.033	–0.024	–0.030	–0.013	0.016	0.005
	(0.043)	(0.049)	(0.037)	(0.042)	(0.026)	(0.032)
Observations	2294	2271	2294	2271	1174	1155
Mean dep. var.	0.19	0.19	0.15	0.15	0.10	0.10
Panel D: Deaths during the day or night	(19)	(20)	(21)	(22)	(23)	(24)
Log(Palestinian deaths at daytime+1)	–0.002	0.036	–0.005	0.004	–0.001	0.025
	(0.033)	(0.039)	(0.023)	(0.029)	(0.023)	(0.026)
Log(Palestinian deaths at nightime+1)	–0.066	–0.015	0.004	0.032	–0.053	–0.036
	(0.059)	(0.081)	(0.036)	(0.048)	(0.045)	(0.065)
Log(Israeli deaths+1)	–0.038	–0.047	–0.034	–0.032	0.006	–0.002
	(0.043)	(0.051)	(0.035)	(0.041)	(0.026)	(0.031)
Observations	1174	1155	1174	1155	1174	1155
Mean dep. var.	0.24	0.25	0.15	0.16	0.10	0.10
All panels: Year-, MoY-, DoW- FEs, Controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a day. Robust standard errors in parentheses. All variables without subscripts are measured at day t. "Year-, MoY-, DoW- FEs," denote fixed effects for each calendar year, each month of the year, and each day of the week. All regressions have the following controls: the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity (we denote this list of covariates as "Controls"). All Panels have the same dependent variables.

Table 3: Exclusion restriction II: Internet outages and news wires

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Log(News wire conflict-zone reports)			Log(All tweets)			Log(Conflict tweets)		
Internet outage	–0.017			–0.180***			–0.181***		
	(0.027)			(0.048)			(0.045)		
Lightning		–0.053			–0.108***			–0.101**	
		(0.038)			(0.042)			(0.047)	
Absence of traffic			–0.006			–0.347***			–0.360***
			(0.034)			(0.088)			(0.078)
Log(Palestinian deaths+1)	0.189***	0.190***	0.171***	0.204***	0.207***	0.154***	0.276***	0.279***	0.210***
	(0.017)	(0.017)	(0.020)	(0.024)	(0.024)	(0.025)	(0.029)	(0.029)	(0.029)
Log(Israeli deaths+1)	0.084	0.081	0.070	0.163***	0.166***	0.146***	0.182**	0.186**	0.159**
	(0.052)	(0.052)	(0.054)	(0.057)	(0.058)	(0.048)	(0.080)	(0.081)	(0.070)
Log(Palestinian deaths+1), t-28 to t-1	0.045***	0.046***	0.041***	0.077***	0.084***	0.066***	0.112***	0.119***	0.099***
	(0.012)	(0.012)	(0.013)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.014)
Log(Israeli deaths+1), t-28 to t-1	0.053***	0.052***	0.052***	0.086***	0.077***	0.108***	0.103***	0.094***	0.128***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.022)	(0.023)	(0.022)	(0.025)
Year-, MoY-, DoW- FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
News agency FEs	✓	✓	✓						
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3866	3866	3515	1291	1291	1174	1291	1291	1174
Mean dep. var.	2.86	2.86	2.85	7.45	7.45	7.45	6.58	6.58	6.58
F-stat, Outages	0.41	1.95	0.03	14.11	6.66	15.40	15.97	4.55	21.46

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a day $\times$ news agency in columns 1 to 3, and a day in columns 4 to 9. Standard errors clustered by date. "Year-, MoY-, DoW- FEs" denote fixed effects for each calendar year, each month of the year, and each day of the week. "News agency FEs" denote fixed effect for each news agency. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.

Table 4: Social media in the conflict zone and the extent of conflict coverage, 2SLS

Dependent variable, all panels:	Prime time coverage	Number of stories	Number of keywords	Length in minutes	Length in minutes	Length in minutes
Panel A: Direct effect only	(1)	(2)	(3)	(4)	(5)	(6)
Sample restriction:					Coverage=1	Deaths<15
Log(Conflict tweets)	0.151**	2.058***	78.588***	38.708***	66.622***	33.103***
	(0.064)	(0.736)	(25.286)	(12.531)	(22.443)	(10.962)
Log(Palestinian deaths+1)	0.064***	1.076***	36.740***	16.166***	15.540*	4.850
	(0.021)	(0.268)	(10.242)	(4.897)	(8.627)	(3.651)
Log(Israeli deaths+1)	0.070**	0.960*	36.345	17.168*	18.897	17.898*
	(0.035)	(0.573)	(23.244)	(10.230)	(16.056)	(10.316)
News pressure	–0.083**	–1.215***	–37.977**	–18.158**	–29.687	–17.003***
	(0.035)	(0.444)	(15.654)	(7.692)	(21.835)	(5.583)
Observations	16900	16900	16900	16900	4153	16720
Mean dep. var.	0.101	0.959	23.186	12.833	52.223	10.929
F-stat, *Internet outage*	20.97	20.97	20.97	20.97	18.22	19.80
Panel B: Interactions with casualties	(7)	(8)	(9)	(10)	(11)	(12)
Sample restriction:					Coverage=1 & Deaths≤15	Deaths<15
Log(Conflict tweets)	0.074	1.113	48.004**	25.143**	40.757**	20.515*
	(0.067)	(0.692)	(22.084)	(11.501)	(19.057)	(10.866)
Log(Conflict tweets) × Log(Palestinian deaths+1)	0.100**	1.235***	37.648*	16.497	36.112**	27.676**
	(0.044)	(0.472)	(22.358)	(10.657)	(16.335)	(13.815)
Log(Conflict tweets) × Log(Israeli deaths+1)	0.051	0.519	33.185	16.133	4.674	16.271
	(0.063)	(0.843)	(31.446)	(14.210)	(32.057)	(16.433)
Log(Palestinian deaths+1)	–0.670**	–7.987**	–240.053	–105.174	–253.632**	–182.466**
	(0.321)	(3.384)	(162.257)	(77.364)	(113.035)	(91.807)
Log(Israeli deaths+1)	–0.309	–2.964	–204.952	–99.716	–11.784	–96.820
	(0.420)	(5.492)	(200.360)	(90.844)	(217.036)	(104.266)
Observations	16900	16900	16900	16900	3983	16720
Mean dep. var.	0.101	0.959	23.186	12.833	45.876	10.929
F-stat, *Internet outage*	14.70	14.70	14.70	14.70	12.09	13.26
F-stat, *Internet outage × Log(PS deaths+1)*	10.79	10.79	10.79	10.79	25.19	16.75
F-stat, *Internet outage × Log(IL deaths+1)*	19.75	19.75	19.75	19.75	13.14	12.06
All panels:						
Network-, Year-, MoY-, DoW- FEs, Controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. All Panels have the same dependent variables. "Network-, Year-, MoY-, DoW- FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity. We restrict the sample to less than 15 casualties in Regression (11), because the first stage is not string enough when the periods of most intense fighting are included if we look only at days and TV networks with conflict coverage. Table B1 presents OLS estimates for the same specifications.

Table 5: Social media and the emotional intensity of conflict coverage, 2SLS

Outcome variables based on:	Contextual sentiment		Use of emotional words			
Panel A: Negative and all emotions	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, this panel:	Negative contextual sentiment		Negative emotions mean		All emotions mean	
Log(Conflict tweets)	3.456**	2.325	0.373*	0.123	0.094	–0.089
	(1.377)	(1.555)	(0.205)	(0.239)	(0.110)	(0.140)
Log(Conflict tweets) × Log(Palestinian deaths+1)		2.090*		0.452**		0.309***
		(1.091)		(0.179)		(0.113)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.275		0.115		0.099
		(2.464)		(0.488)		(0.226)
Log(Palestinian deaths+1)	0.136	–14.758*	0.086	–3.143**	0.108***	–2.107***
	(0.480)	(7.573)	(0.071)	(1.233)	(0.038)	(0.786)
Log(Israeli deaths+1)	1.077	–0.797	0.255**	–0.543	0.163**	–0.531
	(0.693)	(17.133)	(0.127)	(3.411)	(0.071)	(1.559)
Log(Palestinian deaths+1), t-28 to t-1	–0.192	–0.292	–0.015	–0.036	0.018	0.003
	(0.209)	(0.196)	(0.033)	(0.032)	(0.019)	(0.020)
Log(Israeli deaths+1), t-28 to t-1	0.499***	0.607***	0.086***	0.115***	0.035**	0.060***
	(0.163)	(0.217)	(0.027)	(0.039)	(0.017)	(0.023)
Mean dep. var.	15.878	15.592	2.012	1.965	2.560	2.531
Panel B: Positive and neutral emotions	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable, this panel:	Positive contextual sentiment		Positive emotions mean		Neutral emotions mean	
Log(Conflict tweets)	–0.331	–1.003	–0.148	–0.299	0.056	–0.092
	(1.132)	(1.310)	(0.155)	(0.201)	(0.091)	(0.119)
Log(Conflict tweets) × Log(Palestinian deaths+1)		1.032		0.217		0.258***
		(1.015)		(0.164)		(0.096)
Log(Conflict tweets) × Log(Israeli deaths+1)		–0.005		0.181		0.000
		(2.493)		(0.278)		(0.167)
Log(Palestinian deaths+1)	0.525	–7.244	0.139**	–1.452	0.099***	–1.725**
	(0.389)	(7.159)	(0.054)	(1.156)	(0.032)	(0.670)
Log(Israeli deaths+1)	0.421	0.330	0.121	–1.169	0.112*	0.120
	(0.509)	(17.672)	(0.087)	(1.909)	(0.057)	(1.151)
Log(Palestinian deaths+1), t-28 to t-1	0.245	0.168	0.052*	0.039	0.017	0.006
	(0.184)	(0.180)	(0.027)	(0.027)	(0.016)	(0.016)
Log(Israeli deaths+1), t-28 to t-1	–0.031	0.076	–0.003	0.026	0.023	0.039**
	(0.149)	(0.179)	(0.022)	(0.026)	(0.014)	(0.019)
Mean dep. var.	19.643	19.572	3.804	3.787	1.863	1.840
All panels:						
Network-, Year-, MoY-, DoW FEs, Controls	✓	✓	✓	✓	✓	✓
Sample restriction: Days with deaths<15		✓		✓		✓
Observations	4153	3983	4153	3983	4153	3983
F-stat, *Internet outage*	18.22	12.09	18.22	12.09	18.22	12.09
F-stat, *Internet outage × Log(PS deaths+1)*		25.19		25.19		25.19
F-stat, *Internet outage × Log(IL deaths+1)*		13.14		13.14		13.14

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. Negative emotions include anger, fear, disgust and sadness. Neutral emotions include anticipation and surprise. Positive emotions include joy and trust. "Network-, Year-, MoY-, DoW- FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity. Table B2 presents OLS estimates for the same specifications. Table A12 presents 2SLS estimates for each of these emotions separately.

Table 6: Social media and topics in the conflict news (measured by keywords), 2SLS

Panel A: Mentions of civilians	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable, this panel:	The number of keywords on the following topic divided by the total number of words (×100):							
	People*		Children and teenagers*		Civilian casualties*		Terror*	
Log(Conflict tweets)	0.121**	0.106*	0.031**	0.038**	0.003	–0.001	0.062**	0.058*
	(0.055)	(0.064)	(0.013)	(0.017)	(0.003)	(0.003)	(0.027)	(0.032)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.005		–0.011		0.005***		0.014
		(0.040)		(0.014)		(0.002)		(0.021)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.079		–0.004		0.002		–0.015
		(0.072)		(0.034)		(0.006)		(0.040)
Log(Palestinian deaths+1)	–0.023	–0.064	–0.011**	0.072	0.003**	–0.036***	–0.020**	–0.117
	(0.019)	(0.282)	(0.005)	(0.097)	(0.001)	(0.014)	(0.009)	(0.148)
Log(Israeli deaths+1)	–0.022	–0.577	–0.000	0.032	0.001	–0.010	0.003	0.110
	(0.020)	(0.505)	(0.006)	(0.241)	(0.002)	(0.043)	(0.013)	(0.272)
Mean dep. var.	0.330	0.327	0.030	0.029	0.004	0.003	0.067	0.067
Panel B: Mentions of officials	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable, this panel:	The number of keywords on the following topic divided by the total number of words (×100):							
	Hamas*		IL and PS leaders*		US foreign policy off.*		Elections*	
Log(Conflict tweets)	0.051	0.013	0.083**	0.095**	–0.108**	–0.144**	–0.089***	–0.093**
	(0.034)	(0.039)	(0.036)	(0.045)	(0.045)	(0.063)	(0.033)	(0.039)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.058**		–0.027		0.054		0.008
		(0.027)		(0.032)		(0.035)		(0.031)
Log(Conflict tweets) × Log(Israeli deaths+1)		–0.047		–0.013		–0.046		–0.014
		(0.064)		(0.060)		(0.075)		(0.061)
Log(Palestinian deaths+1)	0.022*	–0.401**	–0.025*	0.163	0.034**	–0.355	0.021*	–0.038
	(0.012)	(0.191)	(0.013)	(0.226)	(0.015)	(0.238)	(0.012)	(0.218)
Log(Israeli deaths+1)	0.001	0.331	–0.032**	0.057	0.015	0.324	0.006	0.107
	(0.015)	(0.453)	(0.013)	(0.425)	(0.017)	(0.533)	(0.011)	(0.429)
Mean dep. var.	0.085	0.074	0.102	0.104	0.070	0.069	0.088	0.091
Panel C: Mentions of social media	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Dependent variable, this panel:	The dummy indicating a mention of the following social media:							
	Twitter		Facebook		YouTube		"Social media"	
Log(Conflict tweets)	0.127*	0.068	0.215**	0.194*	–0.021	–0.027	–0.016	–0.070
	(0.076)	(0.082)	(0.090)	(0.103)	(0.047)	(0.045)	(0.055)	(0.070)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.128**		0.026		0.044		0.098*
		(0.060)		(0.088)		(0.041)		(0.052)
Log(Conflict tweets) × Log(Israeli deaths+1)		–0.112		0.006		0.066		–0.101
		(0.132)		(0.174)		(0.098)		(0.127)
Log(Palestinian deaths+1)	0.034	–0.912**	0.009	–0.185	0.034*	–0.291	0.064***	–0.653*
	(0.028)	(0.420)	(0.033)	(0.618)	(0.020)	(0.286)	(0.020)	(0.359)
Log(Israeli deaths+1)	0.009	0.834	–0.025	–0.060	–0.021	–0.482	0.056	0.793
	(0.041)	(0.934)	(0.045)	(1.218)	(0.025)	(0.690)	(0.037)	(0.894)
Mean dep. var.	0.129	0.113	0.149	0.136	0.050	0.046	0.088	0.075
All panels:								
Network-, Year-, MoY-, DoW FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sample: Days with < 15 deaths		✓		✓		✓		
Observations	4153	3983	4153	3983	4153	3983	4153	3983
F-stat, *Internet outage*	18.22	12.09	18.22	12.09	18.22	12.09	18.22	12.09
F-stat, *Internet outage* × *Log(PS deaths+1)*		25.19		25.19		25.19		25.19
F-stat, *Internet outage* × *Log(IL deaths+1)*		13.14		13.14		13.14		13.14

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. Star at the end of the topic denote the fact that there is a number of different keywords associated with this topic. "US foreign policy off." stands for US foreign policy officials. "Network-, Year-, MoY-, DoW FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity. Table B3 presents OLS estimates for the same specifications.

Table 7: Social media and topics of conflict news (measured by LDA machine-learning algorithm), 2SLS

Specification:	1. Direct effect	2. Interactions with casualties			Mean dep. var.
Coefficients on explanatory variables:	Coefficient (SE) on:	Coefficients (SEs) on:			(Prob. of topic)
	log(Conflict tweets)	log(Conflict tweets)	log(Conflict tweets) × log(PS deaths+1)	log(Conflict tweets) × log(IL deaths+1)	
Outcome variable (LDA topic):					
(1) TERRORISM: terrorist / group / kill / Hamas	0.0270**	0.0309**	-0.00715	0.000152	0.0146
	(0.0116)	(0.0144)	(0.00735)	(0.0136)	
(2) IL LEADERSHIP: prime minister / Netanyahu	0.0238*	0.0328*	-0.0199	0.00748	0.0370
	(0.0133)	(0.0171)	(0.0133)	(0.0224)	
(3) ELECTIONS: politics / elections / vote / people	-0.0687***	-0.0729***	0.00606	0.0156	0.0466
	(0.0211)	(0.0262)	(0.0178)	(0.0306)	
(4) SETTLEMENTS: settlements / [west] bank / construct	-0.0205*	-0.0251*	0.00420	0.0247	0.0234
	(0.0116)	(0.0143)	(0.0102)	(0.0234)	
(5) US FOREIGN POLICY: secretary of state / report / Kerry	-0.0455*	-0.0594*	0.0278	-0.00520	0.0569
	(0.0233)	(0.0310)	(0.0199)	(0.0343)	
(6) OBAMA: president Obama / white house	0.00957	0.0371	-0.0491*	0.00604	0.0825
	(0.0233)	(0.0300)	(0.0287)	(0.0507)	
(7) ATTACKS [1]: air strike / fire / rocket / people	0.00993	-0.0130	0.0440***	-0.0639*	0.0225
	(0.0103)	(0.0127)	(0.0140)	(0.0382)	
(8) ATTACKS [2]: report / people / attack / kill / government	0.00593	-0.00219	0.0243	-0.0345	0.0688
	(0.0188)	(0.0229)	(0.0188)	(0.0436)	
(9) ATTACKS [3]: Hamas / rocket / civilian / iron dome	-0.00681	-0.0112	0.00206	0.0282	0.0109
	(0.00817)	(0.00780)	(0.00871)	(0.0214)	
(10) ATTACKS [4]: tunnel / Hamas / fire / soldier / people	0.00435	-0.00121	0.0106	-0.0220	0.0161
	(0.00708)	(0.00772)	(0.00742)	(0.0270)	
(11) All topics on ATTACKS together: [1]+[2]+[3]+[4]	0.0134	-0.0276	0.0810**	-0.0923	0.118
	(0.0283)	(0.0340)	(0.0328)	(0.0937)	
All regressions with this specification:					
Number of observations:	4,153	3,983			
F-stat, internet outage:	18.22	12.09			
F-stat, internet outage × log(PS deaths+1):		25.19			
F-stat, internet outage × log(IL deaths+1):		13.14			

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. Each row presents results of two specifications for the outcome variables listed in the first column. Every regression includes the following controls: fixed effects for each TV network, each calendar year, each month of the year, and each day of the week, the logs of (1+) Palestinian and Israeli deaths at day t, as well as between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity. Table A13 in the Online Appendix presents the results for the rest of the LDA topics. Table B4 presents OLS estimates for the same specifications.

Table 8: Social media and details in and similarity of conflict news across outlets, 2SLS

Panel A: Mentions of details	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, this panel:	The number of keywords on heavy ammunition* in total words (×100)		Dummy for mentions of concrete small geographic locations in: Israel		Palestinian Territor.	
Log(Conflict tweets)	0.008	–0.075	0.194	0.151	0.080	0.012
	(0.049)	(0.060)	(0.119)	(0.138)	(0.077)	(0.084)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.131***		0.039		0.130**
		(0.050)		(0.105)		(0.063)
Log(Conflict tweets) × Log(Israeli deaths+1)		–0.014		0.104		–0.162
		(0.165)		(0.212)		(0.189)
Log(Palestinian deaths+1)	0.091***	–0.856**	0.003	–0.262	0.028	–0.902**
	(0.018)	(0.349)	(0.041)	(0.735)	(0.028)	(0.437)
Log(Israeli deaths+1)	0.015	0.115	0.090**	–0.655	0.063	1.185
	(0.029)	(1.185)	(0.044)	(1.505)	(0.041)	(1.354)
Sample: Days with < 15 deaths		✓		✓		✓
Mean dep. var.	0.175	0.154	0.268	0.258	0.123	0.111
Observations	4153	3983	4153	3983	4153	3983
F-stat, *Internet outage*	18.22	12.09	18.22	12.09	18.22	12.09
F-stat, *Internet outage × Log(PS deaths+1)*		25.19		25.19		25.19
F-stat, *Internet outage × Log(IL deaths+1)*		13.14		13.14		13.14
Panel B: Similarity across networks	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable, this panel:	Similarity of conflict-related stories by US TV networks to:					
	other US TV networks		to Al Jazeera		to Al Jazeera	
Sample, US TV networks considered:	All		All		CNN, FOX, and PBS	
Log(Conflict tweets)	0.050	–0.004	0.094*	0.091	0.140**	0.142*
	(0.043)	(0.046)	(0.054)	(0.061)	(0.066)	(0.077)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.088**		0.008		–0.005
		(0.040)		(0.020)		(0.027)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.020		–0.027		–0.069
		(0.084)		(0.053)		(0.065)
Log(Palestinian deaths+1)	0.027*	–0.617**	0.012	–0.050	0.004	0.043
	(0.015)	(0.286)	(0.013)	(0.159)	(0.016)	(0.209)
Log(Israeli deaths+1)	0.023	–0.113	0.005	0.218	0.016	0.544
	(0.019)	(0.591)	(0.020)	(0.404)	(0.019)	(0.485)
Sample: Days with < 15 deaths		✓				
Mean dep. var.	0.450	0.440	0.381	0.381	0.385	0.385
Observations	3466	3296	1551	1551	908	908
F-stat, *Internet outage*	17.77	13.44	12.58	13.56	11.65	12.27
F-stat, *Internet outage × Log(PS deaths+1)*		24.92		29.21		21.82
F-stat, *Internet outage × Log(IL deaths+1)*		14.97		25.24		20.89
All panels:						
Network-, Year-, MoY-, DoW FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. Star at the end of the topic denote the fact that there is a number of different keywords associated with this topic. "Network-, Year-, MoY-, DoW FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity. Table B5 presents OLS estimates for the same specifications.

Table 9: Social media and the mentions of civilian casualties in conflict news depending on the number of casualties across the entire sample, 2SLS

	(1)	(2)	(3)
Dependent variable:	The dummy indicating mentions of civilian casualties*		
Log(Conflict tweets)		0.053	–0.002
		(0.036)	(0.036)
Log(Conflict tweets) × Number of Palestinian deaths			0.037***
			(0.009)
Log(Conflict tweets) × Number of Israeli deaths			0.049***
			(0.018)
Number of Palestinian deaths	0.027***	0.020***	–0.250***
	(0.005)	(0.006)	(0.062)
Number of Israeli deaths	0.047**	0.044**	–0.290***
	(0.022)	(0.022)	(0.111)
Network-, Year-, MoY-, DoW FEs	✓	✓	✓
Controls	✓	✓	✓
Sample: Days with < 15 deaths	✓	✓	✓
Observations	16720	16720	16720
Mean dep. var.	0.029	0.029	0.029
F-stat, *Internet outage*		18.19	14.47
F-stat, *Internet outage × Number of PS deaths*			27.74
F-stat, *Internet outage × Number of IL deaths*			40.55

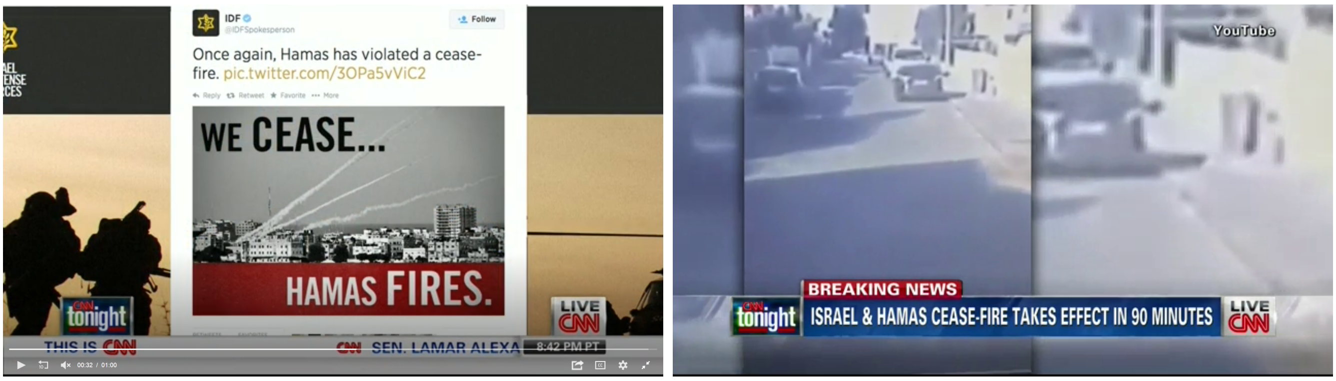
Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is TV network × date. Standard errors clustered at date level in parentheses. Star at the end of the topic denote the fact that there is a number of different keywords associated with this topic. "Network-, Year-, MoY-, DoW FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. All regressions also control for news pressure, dummy for other conflicts involving Israel, and rain and wind intensity (denoted by "Controls").

A Online Appendix

Figure A1: CNN quotes from Twitter account of a 16-year-old Farah Baker, who describes life in Gaza during the 2014 Gaza war

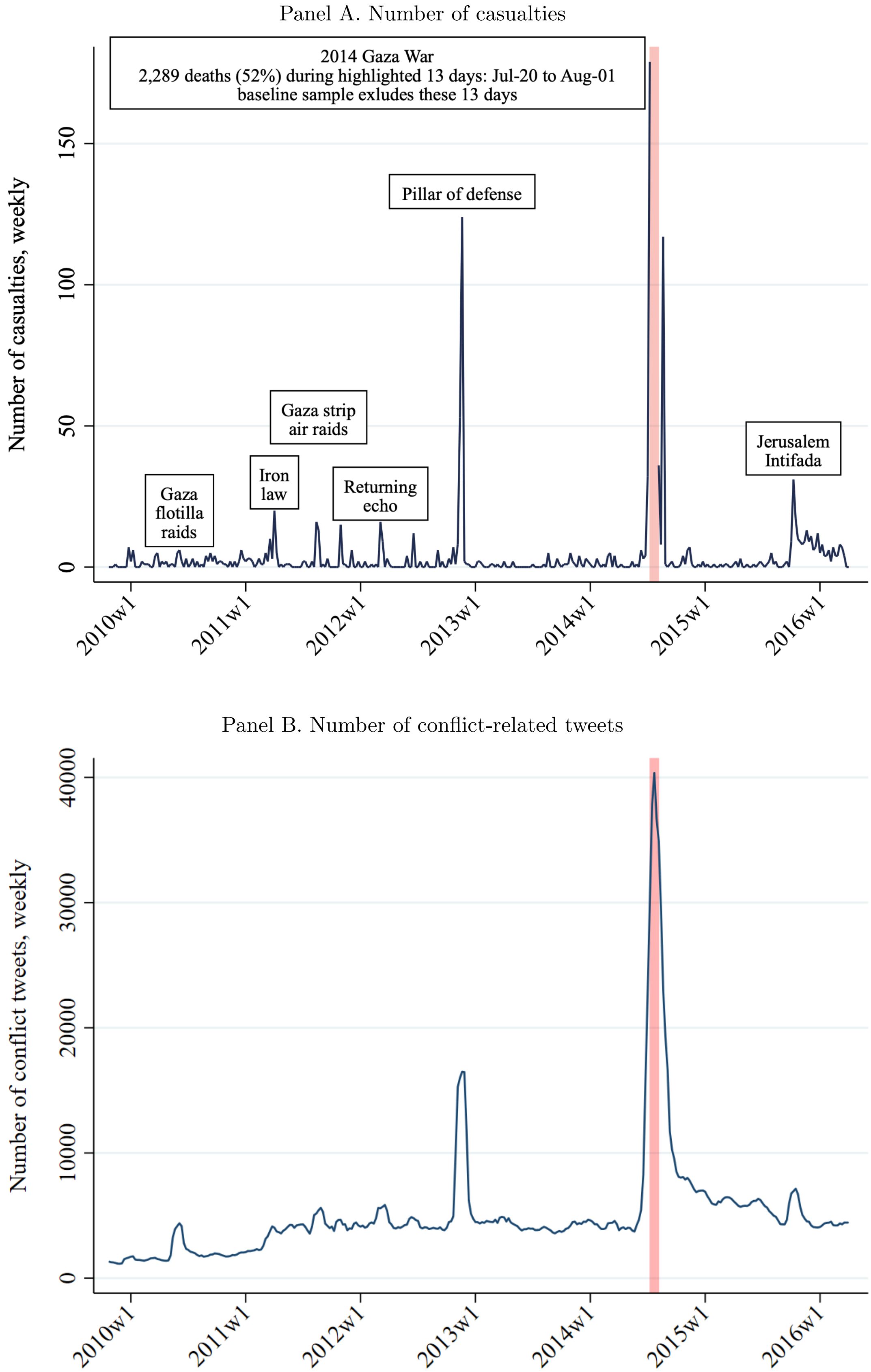
Source: Screenshots from CNN broadcast, available at: https://edition.cnn.com/videos/world/2014/07/31/nr-bts-life-of-gaza-resident-farah-baker.cnn, accessed March 12, 2021.

Figure A2: CNN uses content from the Twitter account of the Israeli Defense Forces and YouTube footage of the conflict zone



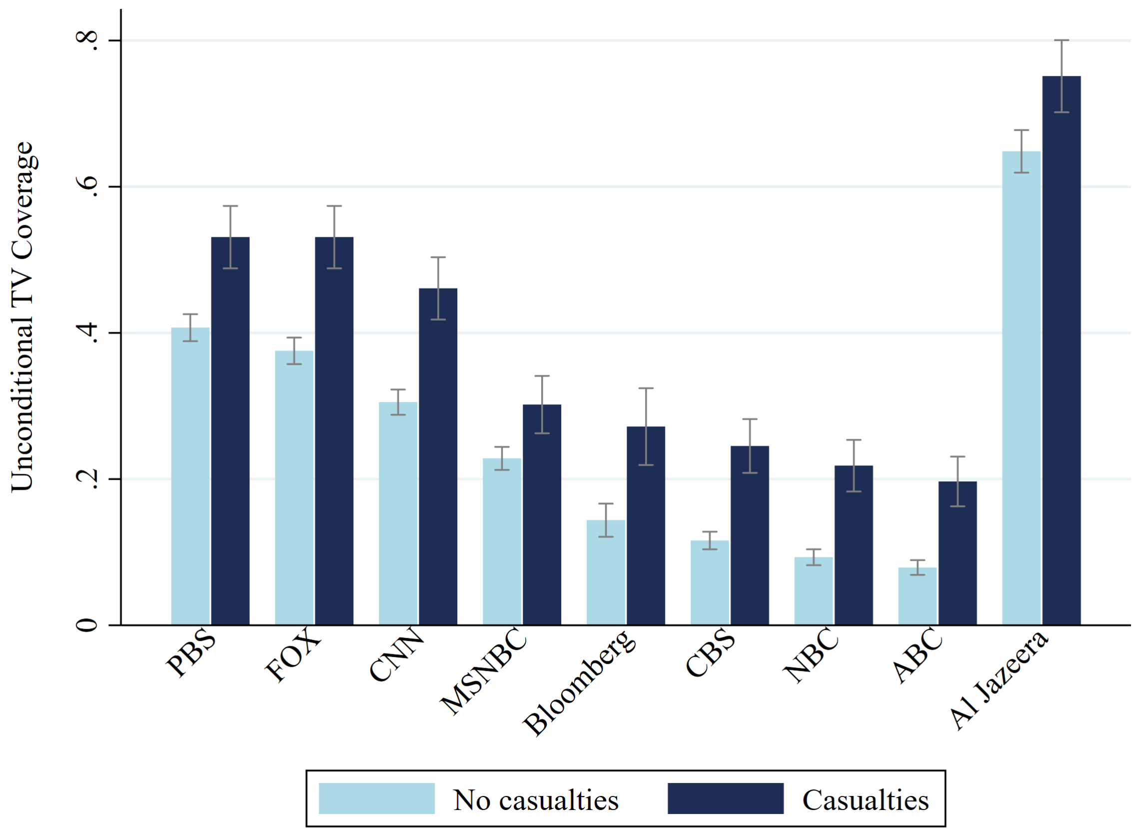
Source: US Television News Archive.
See https://archive.org/details/CNNW_20140808_030000_Anderson_Cooper_360/start/2520/end/2580 and https://archive.org/details/CNNW_20140801_030000_Anderson_Cooper_360/start/1930/end/1990, both accessed May 13, 2021.

Figure A3: Casualties and conflict-related tweets over time



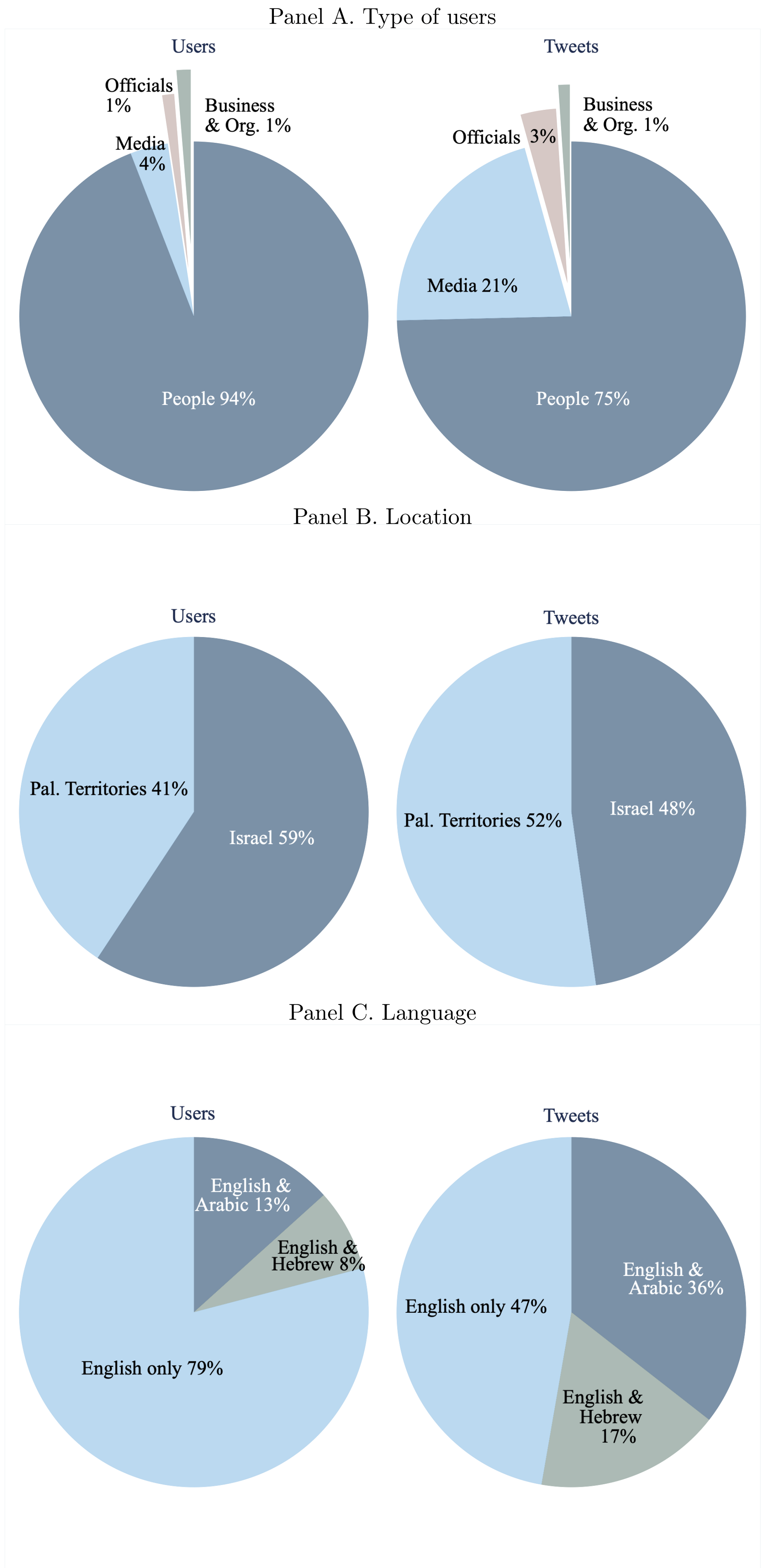
Note: Shaded area indicates the two weeks of the most intense fighting over the observation period, when 2,289 people died during two-week period (the scale of the y-axis does not allow showing them on the graph). "w1" indicates the first week of each year on the x-axis.

Figure A4: TV coverage and conflict events



Note: The figure presents the daily probability of coverage of the conflict zone by network separately for days with and without casualties on either side of the conflict.

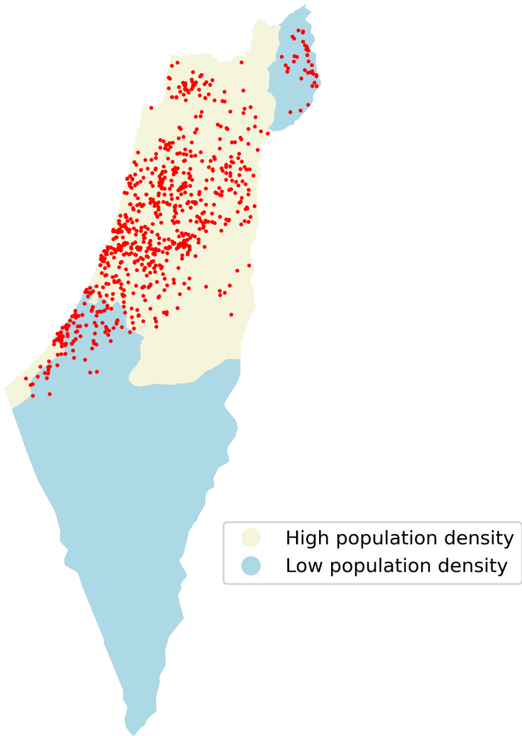
Figure A5: The composition of user accounts and conflict tweets by characteristics of users



Note: The difference between the composition of users and the composition of (conflict-related) tweets arises from the fact that some users tweet more than others.

Figure A6: Lightning strikes in the conflict zone

Panel A. An example of a day with a thunderstorm: a map of locations of lightning strikes on November 16, 2014



Panel B. Average number lightning strikes by calendar month

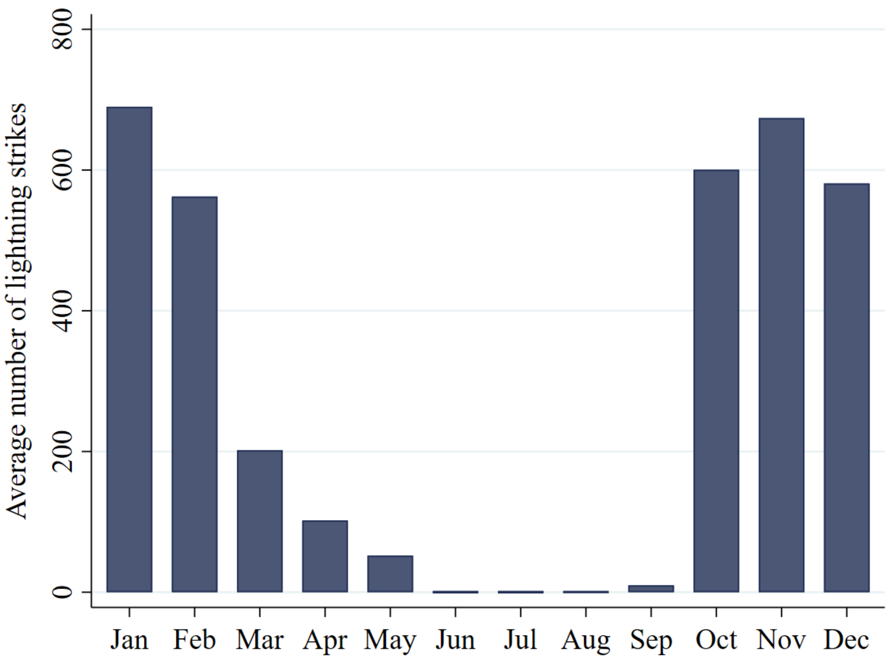
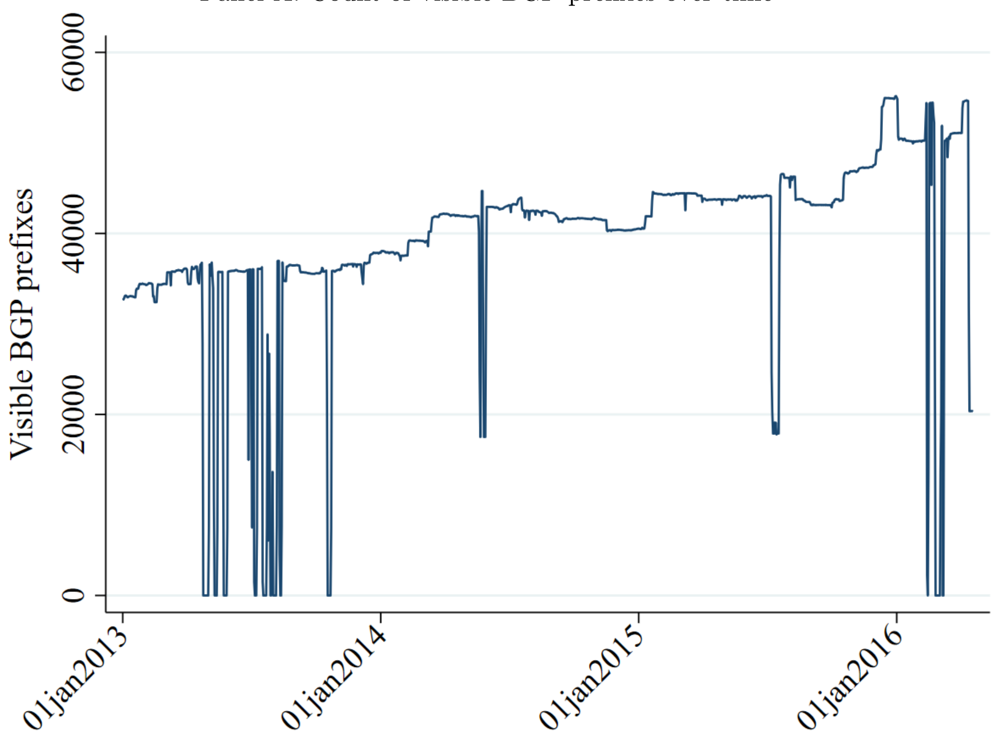
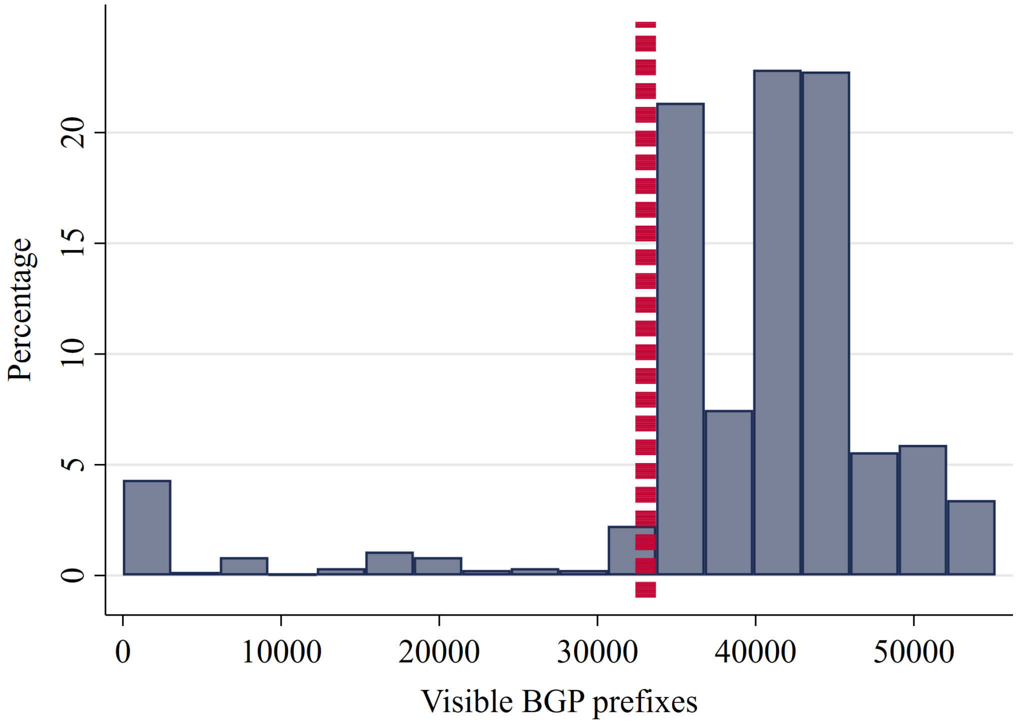


Figure A7: Internet traffic between Israel and Palestine and the rest of the WWW

Panel A. Count of visible BGP prefixes over time

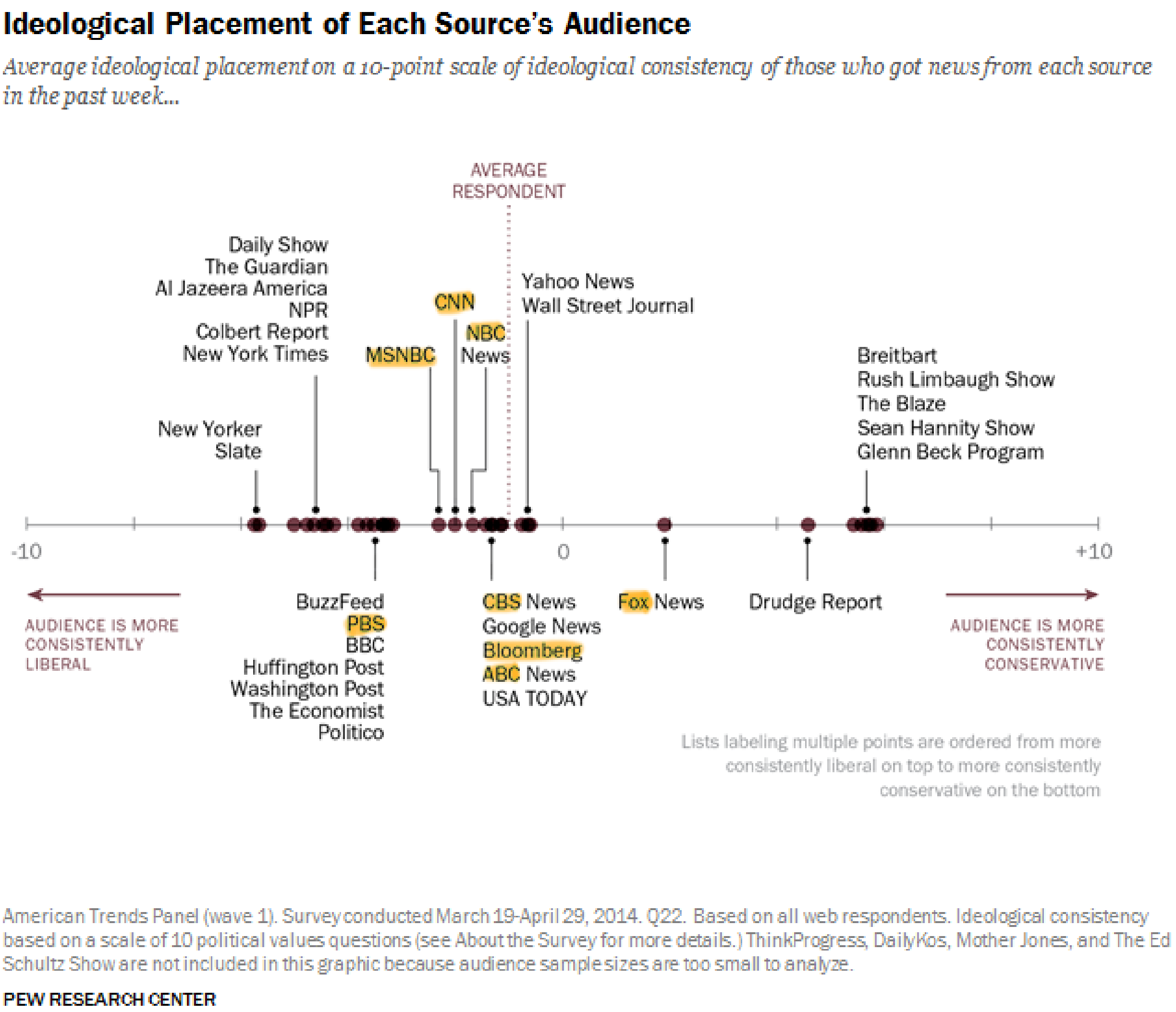


Panel B. Distribution of the count of visible BGP prefixes
and the threshold defining the absence of traffic



Note: Panel A of the figure presents the daily internet traffic between Israeli and Palestinian autonomous systems and the rest of the WWW on a timeline. Panel B presents the distribution of this variable and the cut-off that we use to define the days without visible traffic.

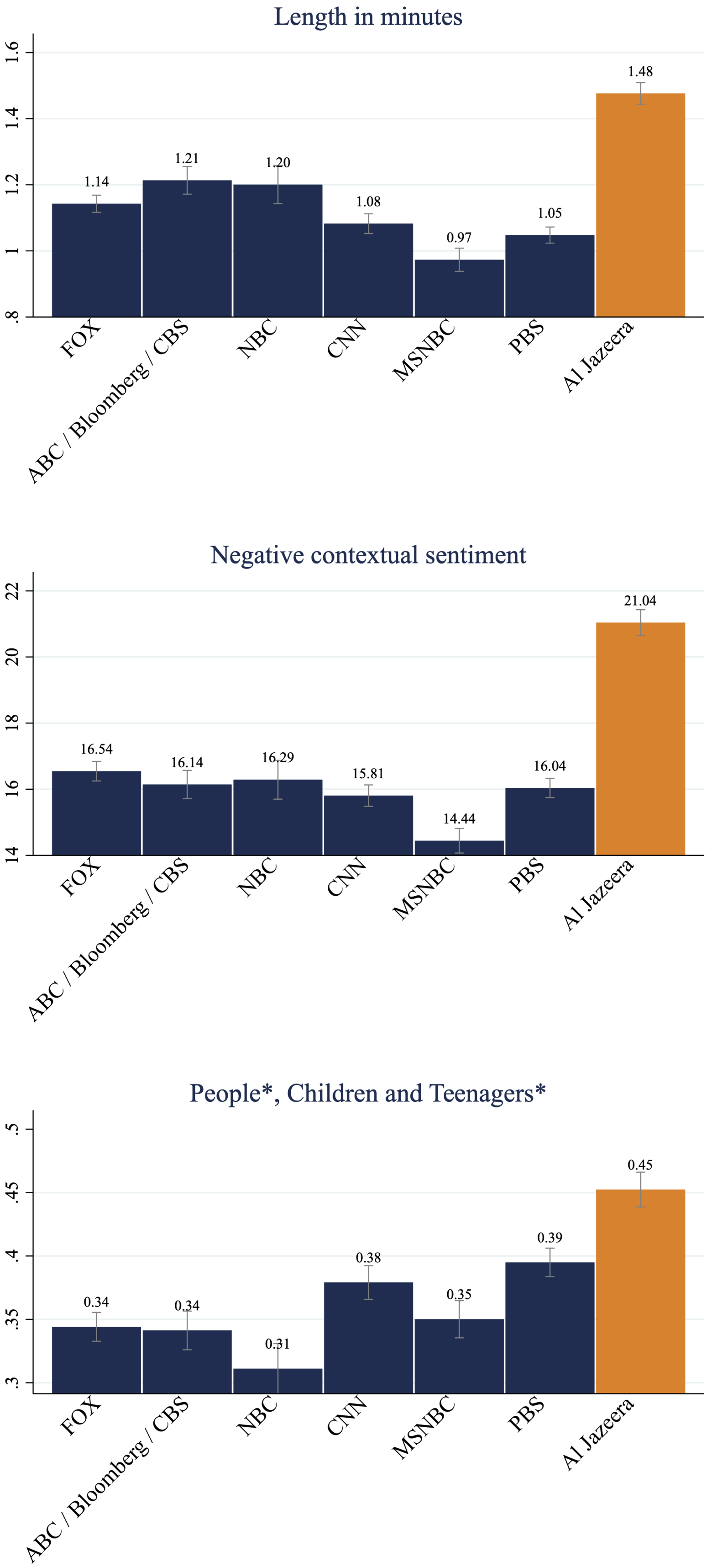
Figure A8: Liberal-conservative ideology of the channels' viewers, PEW Research Center (2014)



Note: The figure presents the PEW Research Center's ranking of the ideology of the audience of US TV networks. The networks data for which are used in the paper are highlighted orange.

Source: https://www.pewresearch.org/pj_14-10-21_mediapolarization-08-2/ (accessed March 21, 2021).

Figure A9: Summary statistics of conflict coverage across networks



Note: The figure presents the means of the length, negative contextual sentiment score, and mentions of civilians in the conflict news by TV network. US networks are sorted from conservative to liberal.

Table A1: Summary statistics across days

	Observations (Network × Day)	Mean	Standard deviation	Median	Min	Max
Social media in the conflict zone:						
Log(All tweets)	2294	7.25	0.57	7.36	1.61	9.29
Log(Conflict tweets)	2294	6.32	0.66	6.38	0.69	8.97
Share of tweets (x100) by people	2294	71.06	7.64	72.21	39.84	89.25
Share of tweets (x100) by media	2294	24.28	6.76	23.42	8.27	60.00
Share of tweets (x100) by officials	2294	3.63	3.16	2.94	0.00	45.34
Share of tweets (x100) of all users from Palestine	2294	51.30	11.01	51.91	0.00	88.93
Share of tweets (x100) of all users in English only	2294	45.22	9.08	45.01	13.49	77.39
Share of tweets (x100) of all users in English + Arabic	2294	35.62	9.84	34.78	0.00	75.15
Share of tweets (x100) of ordinary people from Palestine	2294	53.82	12.70	55.21	0.00	100.00
Share of tweets (x100) of ordinary people in English only	2294	45.60	10.35	45.20	0.00	80.11
Share of tweets (x100) of ordinary people in English + Arabic	2294	37.72	12.00	37.81	0.00	85.71
Outages:						
Internet outage	2294	0.19	0.39	0	0	1
Lightning	2294	0.15	0.35	0	0	1
Absence of traffic	1174	0.10	0.30	0	0	1
BGP Prefixes count (/ 1000)	1174	38.76	10.95	42	0	55
Controls:						
Log(Palestinian deaths+1)	2294	0.18	0.51	0.00	0.00	4.61
Log(Israeli deaths+1)	2294	0.02	0.14	0.00	0.00	1.79
Log(Palestinian deaths+1), t-28 to t-1	2294	1.83	1.21	1.61	0.00	7.63
Log(Israeli deaths+1), t-28 to t-1	2294	0.47	0.72	0.00	0.00	4.19
Log(Palestinian civilian deaths+1)	2294	0.13	0.43	0.00	0.00	4.36
Log(Palestinian non-civilian deaths+1)	2294	0.08	0.35	0.00	0.00	3.40
Log(Palestinian female deaths+1)	2294	0.02	0.17	0.00	0.00	2.89
Log(Palestinian male deaths+1)	2294	0.16	0.47	0.00	0.00	4.04
Log(Palestinian child deaths+1)	2294	0.03	0.23	0.00	0.00	3.33
Log(Palestinian deaths at daytime+1)	1174	0.15	0.39	0.00	0.00	3.18
Log(Palestinian deaths at nightime+1)	1174	0.04	0.18	0.00	0.00	1.95
News pressure	2294	0.40	0.13	0.37	0.08	1.00
Other conflict with Israel	2294	0.04	0.19	0	0	1
Share of population with rain	2294	0.16	0.24	0.00	0.00	1.00
Mean wind speed	2294	0.23	0.07	0.23	0.00	0.73
News wires conflict-zone reports:						
Log(Reuters report)	1285	2.96	0.66	3.09	0.00	4.77
Log(American Press report)	1291	2.85	0.56	2.83	1.10	4.33
Log(Agence France Press report)	1290	2.77	0.66	2.83	0.00	4.87
Islamic prayer bot:						
Prayer bot did not tweet (when scheduled)	1682	0.08	0.27	0	0	1

Table A2: Summary statistics across all US TV networks and days

	Observations (Network × Day)	Mean	Standard deviation	Median	Min	Max
The extent of coverage of the conflict zone by US TV news:						
Prime time coverage	16900	0.10	0.30	0	0	1
Number of stories	16900	0.96	2.83	0	0	54
Number of keywords	16900	23.19	104.63	0	0	3340
Length in minutes	16900	12.83	49.81	0	0	1316
Social media in the conflict zone:						
Log(All tweets)	16900	7.26	0.57	7.36	1.61	9.29
Log(Conflict tweets)	16900	6.34	0.67	6.39	0.69	8.97
Outages:						
Internet outage	16900	0.19	0.39	0	0	1
Lightning	16900	0.15	0.35	0	0	1
Absence of traffic	9059	0.10	0.30	0	0	1
Controls:						
Log(Palestinian deaths+1)	16900	0.18	0.52	0.00	0.00	4.61
Log(Israeli deaths+1)	16900	0.02	0.15	0.00	0.00	1.79
Log(Palestinian deaths+1), t-28 to t-1	16900	1.85	1.23	1.61	0.00	7.63
Log(Israeli deaths+1), t-28 to t-1	16900	0.48	0.73	0.00	0.00	4.19
News pressure	16900	0.40	0.13	0.37	0.08	1.00
Other conflict involving Israel	16900	0.04	0.19	0	0	1
Share of population with rain	16900	0.16	0.24	0.01	0.00	1.00
Mean wind speed	16900	0.23	0.07	0.23	0.00	0.73
Other variables used in the robustness checks:						
Prime time coverage, from Vanderbilt	9176	0.02	0.14	0	0	1
Length in minutes, from Vanderbilt	9176	0.07	0.95	0.00	0.00	42.50

Table A3: Summary statistics across all networks and days with conflict-related broadcast

	Sample: days × US TV networks with conflict-related news					
	Observations (Network × Day)	Mean	Standard deviation	Median	Min	Max
Score of emotional intensity, measured by the use of emotional words (1-100):						
Negative emotions, mean	4153	2.01	0.85	1.85	0.37	6.09
Positive emotions, mean	4153	3.80	0.66	3.79	1.80	6.81
Neutral emotions, mean	4153	1.86	0.44	1.82	0.67	3.90
All emotions, mean	4153	2.56	0.50	2.51	1.29	4.63
Anger	4153	2.15	1.00	1.96	0.23	8.19
Fear	4153	2.85	1.27	2.63	0.15	8.23
Disgust	4153	1.02	0.49	0.94	0.06	3.86
Sadness	4153	2.03	0.81	1.87	0.45	6.35
Anticipation	4153	2.56	0.57	2.53	0.50	5.46
Surprise	4153	1.16	0.47	1.08	0.11	4.47
Joy	4153	2.68	0.68	2.63	0.89	6.87
Trust	4153	4.93	0.91	4.90	1.78	8.78
Score of contextual sentiment (1-100):						
Negative contextual sentiment	4153	15.88	5.55	15.40	1.30	43.70
Positive contextual sentiment	4153	19.64	5.07	19.70	2.80	44.10
Topics measured by keywords, number of keywords on a topic in 100 words:						
People*	4153	0.33	0.21	0.30	0.00	1.28
Children and teenagers*	4153	0.03	0.06	0.00	0.00	0.33
Civilian casualties*	4153	0.00	0.01	0.00	0.00	0.11
Terror*	4153	0.07	0.11	0.02	0.00	0.56
Hamas*	4153	0.09	0.15	0.00	0.00	0.73
IL and PS leaders*	4153	0.10	0.14	0.06	0.00	0.83
US foreign policy officials*	4153	0.07	0.13	0.00	0.00	1.02
Elections*	4153	0.09	0.13	0.04	0.00	0.87
Heavy ammunition*	4153	0.18	0.23	0.09	0.00	1.59
Dummy for mention of the following social media:						
Twitter	4153	0.13	0.33	0	0	1
Facebook	4153	0.15	0.36	0	0	1
Youtube	4153	0.05	0.22	0	0	1
"Social media"	4153	0.09	0.28	0	0	1
Dummy for mention of concrete small geographic locations in:						
Israel	4153	0.27	0.44	0	0	1
Palestinian Territories	4153	0.12	0.33	0	0	1
Similarity across networks:						
US network's similarity to other US networks	3466	0.45	0.15	0.00	0.11	0.93
US network's similarity to Al Jazeera	1551	0.38	0.11	0.00	0.13	0.66

Table A4: Summary statistics of the LDA topics across all networks and days with conflict-related broadcast

Sample: days × US TV networks with conflict-related news

LDA topic: label	Most frequent stemmed keywords	Observations (Network × Day)	Mean	Standard deviation	Median	Min	Max
TERRORISM: terrorist / group / kill / Hamas	hama, terrorist, terror, group, organ, attack, support, govern, kill, terrorist organ	4153	0.01	0.03	0.00	0.00	0.48
IL LEADERSHIP: prime minister / Netanyahu	minist, prime, prime minist, netanyahu, isra, minist netanyahu, isra prime, state, deal, govern	4153	0.04	0.05	0.02	0.00	0.50
ELECTIONS: politics / elections / vote / people	peopl, elect, parti, right, polit, vote, countri, thing, support, govern	4153	0.05	0.07	0.02	0.00	0.66
SETTLEMENTS: settlements / [west] bank / construct	jerusalem, settlement, bank, isra, peac, talk, news, year, world, east	4153	0.02	0.05	0.00	0.00	0.59
US FOREIGN POLICY: secretary of state / report / Kerry	report, new, state, secretari, offici, news, kerri, time, hous, depart	4153	0.06	0.08	0.03	0.00	0.57
OBAMA: president Obama / white house	presid, obama, presid obama, hous, white, white hous, state, clinton, polici, new	4153	0.08	0.10	0.05	0.00	0.62
ATTACKS [1]: air strike / fire / rocket / people	fire, rocket, peopl, strike, isra, air, ground, air strike, report, day	4153	0.02	0.05	0.00	0.00	0.50
ATTACKS [2]: report / people / attack / kill / government	report, govern, peopl, kill, forc, war, attack, countri, militari, group	4153	0.07	0.10	0.02	0.00	0.75
ATTACKS [3]: Hamas / rocket / civilian / iron dome	hama, rocket, civilian, isra, fire, missil, war, defens, iron, dome	4153	0.01	0.03	0.00	0.00	0.53
ATTACKS [4]: tunnel / Hamas / fire / soldier / people	hama, fire, isra, tunnel, peopl, fight, soldier, kill, hour, militari	4153	0.02	0.04	0.00	0.00	0.48
International law / UN	nation, unit nation, council, unit, secur council, intern, abba, general, assembl, secur	4153	0.01	0.03	0.00	0.00	0.32
Family / prison / courts	year, famili, prison, court, old, year old, case, home, isra, death	4153	0.03	0.07	0.01	0.00	0.90
State / peace / negotations	state, peopl, peac, unit, isra, unit state, presid, negoti, time, way	4153	0.16	0.18	0.11	0.00	0.96
Police / killing	polic, attack, kill, report, shot, man, peopl, offic, year, old	4153	0.04	0.08	0.00	0.00	0.67
People / time / US/ right thing	peopl, time, thing, right, us, way, good, world, new, year	4153	0.13	0.13	0.09	0.00	0.81
Plane crash	flight, plane, crash, airlin, airport, investig, passeng, site, air, shot	4153	0.01	0.02	0.00	0.00	0.26
Greetings	morn, good, good morn, new, day, report, storm, rain, weather, hour	4153	0.04	0.08	0.01	0.00	0.74
Nuclear weapons / nuclear deal	nuclear, weapon, deal, nuclear weapon, program, world, presid, unit, militari, unit state	4153	0.04	0.09	0.00	0.00	0.72
Border crossing / children	children, border, crisi, countri, cross, law, kid, hous, problem, cross border	4153	0.01	0.02	0.00	0.00	0.23
Violence / Israel / Jerusalem	isra, jerusalem, violenc, attack, secur, bank, situat, forc, tension, us	4153	0.02	0.05	0.00	0.00	0.46
Doctor / insurance / medical	doctor, insur, pain, right, medic, blood, plan, heart, problem, day	4153	0.03	0.06	0.00	0.00	0.57
Economy / market	tax, year, economi, market, busi, job, money, compani, econom, week	4153	0.04	0.07	0.01	0.00	0.68
Local conditions: water / food	peopl, water, citi, bay, food, area, church, communiti, year, land	4153	0.03	0.06	0.00	0.00	0.64
Schools	school, student, year, old, year old, day, right, high, peopl, counti	4153	0.02	0.04	0.00	0.00	0.44
Energy / gulf	oil, ship, gas, gulf, coast, price, isra, water, aid, activist	4153	0.01	0.02	0.00	0.00	0.29

Table A5: Summary statistics: US TV news about the conflict zone

Network	Obs. (Days)	Dummy: Coverage Mean	Number of TV News Stories: Mean	Min	Max	Mean if covered
All US networks	2,294	0.25	0.96	0	54	3.90
PBS	2,294	0.43	1.55	0	30	3.64
FOX	2,294	0.40	1.73	0	54	4.31
CNN	2,294	0.33	1.28	0	35	3.86
MSNBC	2,294	0.24	0.79	0	28	3.30
Bloomberg	842	0.17	0.41	0	13	2.34
CBS	2,294	0.14	0.62	0	26	4.54
NBC	2,294	0.11	0.49	0	26	4.33
ABC	2,294	0.10	0.45	0	23	4.64
Al Jazeera America	937	0.67	4.16	0	25	6.19

Note: The table presents the summary statistics for the extent of coverage of the Israeli-Palestinian conflict by the US TV networks across days in the sample.

Table A6: List of stemmed keywords used to measure topic coverage

Topic:	Stemmed keyword(s) included in the topic:
People*	people; civilian
Children and teenagers*	young Israeli; young Palestinian; kid; Palestinian child; Israeli child; -old child; -old baby; baby girl; baby boy
Civilian casualties*	civilian killed; innocent civilian; civilian casualt; civilian death; people died; people killed; civilian victim; civilian died
Terror*	terror
Hamas*	Hamas
IL and PS leaders*	Israeli government; Israeli leader; Netanyahu; Palestinian government; Palestinian leader; Palestinian president; Abbas
US foreign policy officials*	secretary of state; secretary Clinton; secretary Kerry; Hillary Clinton; Kerry
Elections*	elect; vote
Heavy ammunition*	artillery; air strike; fire; bomb; tank; rocket; missile

Table A7: Performance of the algorithm classifying tweets into conflict-related and conflict-unrelated

	Machine coding (Naive Bayes algorithm)	Human coding (Research assistant)
Accuracy	0.80	0.80
Precision	0.85	0.92
Recall	0.82	0.79
F-score	0.83	0.85

Note: The table presents the comparison of performance of machine coding and human coding by a research assistant for the algorithm classifying the tweets into conflict-related and conflict-unrelated. *Accuracy* is defined as the share of correctly classified tweets. *Precision* is defined as the share of true positives among all selected elements. Precision reflects how many tweets classified as conflict-related actually are conflict-related. *Recall* is defined as a share of true positives among all relevant elements. Recall reflects how many of all conflict-related tweets are classified as conflict-related. *F-score*= $2\frac{\sqrt{Precision \times Recall}}{Precision+Recall}$. The Lidstone smoothing hyper-parameter α is chosen to maximize F-score.

Table A8: Verification that the "BGP Prefix Count" is not driven by demand for internet use

Panel A: Weekends versus week days	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, this panel:	Log(All tweets)			BGP Prefix Count / 1000		
Weekend	–0.264***	–0.264***	–0.267***	0.082	0.238	0.160
	(0.034)	(0.030)	(0.027)	(0.713)	(0.572)	(0.555)
Year, MoY FEs		✓	✓		✓	✓
Controls			✓			✓
Observations	1174	1174	1174	1174	1174	1174
Mean dep. var.	7.45	7.45	7.45	38.76	38.76	38.76
Panel B: Day versus night time	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable, this panel:	Log(Hourly number of all tweets)			Hourly BGP Prefix Count / 1000		
Day time	0.676***	0.676***	0.675***	–0.008	–0.008	–0.008
	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)	(0.005)
Year, MoY, DoW FEs		✓	✓		✓	✓
Controls			✓			✓
Observations	2343	2343	2343	2348	2348	2348
Mean dep. var.	4.09	4.09	4.09	1.62	1.62	1.62

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is a day in panel A, and a day × day/night time in panel B. Dependent variable in Regressions 7 to 9 is the average of the log(Hourly number of all tweets) at day × day/night time level. Dependent variable in Regressions 10 to 12 is the average of (Hourly BGP Prefix Count / 1000) at day × day/night time level. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths at day t, as well as between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.

Table A9: Compliers I: Which types of users are affected by internet outages?
All Twitter users are classified into:
ordinary people, media, officials, businesses, and organizations

Dependent variable:	The share of tweets (x100) by: people	media	officials
Panel A: Internet Outages	(1)	(2)	(3)
Internet outage	–1.329***	1.232***	0.139
	(0.349)	(0.328)	(0.132)
R-squared	0.57	0.52	0.33
Observations	2294	2294	2294
Mean dep. var.	71.06	24.28	3.63
Panel B: Lightning Strikes	(4)	(5)	(6)
Lightning strike	–0.792*	0.887**	–0.062
	(0.414)	(0.371)	(0.160)
R-squared	0.57	0.52	0.33
Observations	2294	2294	2294
Mean dep. var.	71.06	24.28	3.63
Panel C: Absence of Traffic	(7)	(8)	(9)
Absence of traffic	–1.920***	1.651***	0.420**
	(0.557)	(0.538)	(0.193)
R-squared	0.34	0.35	0.39
Observations	1174	1174	1174
Mean dep. var.	74.07	21.44	3.06
Year, MoY, DoW FEs	✓	✓	✓
Controls	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a day. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths at day t, as well as between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.

Table A10: Compliers II: Palestinian and Israeli users are equally affected by internet outages

Dependent variable:	Share of tweets (x100) by accounts:					
	of all users			of ordinary people		
	from Palestine	in English only	in Eng.+Arabic	from Palestine	in English only	in Eng.+Arabic
Accounts classified by:	Geography:	Language:		Geography:	Language:	
	PS or IL	Eng., Eng.+Arabic, Eng.+Hebrew		PS or IL	Eng., Eng.+Arabic, Eng.+Hebrew	
Panel A: Internet Outages	(1)	(2)	(3)	(4)	(5)	(6)
Internet outage	0.066	0.343	–0.450	0.424	0.184	–0.131
	(0.567)	(0.372)	(0.494)	(0.665)	(0.524)	(0.643)
R-squared	0.46	0.61	0.48	0.46	0.44	0.44
Observations	2294	2294	2294	2294	2294	2294
Mean dep. var.	51.30	45.22	35.62	53.82	45.60	37.72
Panel B: Lightning Strikes	(7)	(8)	(9)	(10)	(11)	(12)
Lightning strike	0.666	0.142	–0.073	0.916	0.004	0.033
	(0.697)	(0.480)	(0.605)	(0.794)	(0.659)	(0.775)
R-squared	0.46	0.61	0.48	0.46	0.44	0.44
Observations	2294	2294	2294	2294	2294	2294
Mean dep. var.	51.30	45.22	35.62	53.82	45.60	37.72
Panel C: Absence of Traffic	(13)	(14)	(15)	(16)	(17)	(18)
Absence of traffic	–0.665	–0.169	0.033	–0.173	–0.708	0.738
	(0.949)	(0.705)	(0.868)	(1.081)	(1.008)	(1.072)
R-squared	0.37	0.46	0.41	0.31	0.46	0.41
Observations	1174	1174	1174	1174	1174	1174
Mean dep. var.	51.84	50.96	32.23	56.62	49.54	35.97
Year, MoY, DoW FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a day. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths at day t, as well as between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.

Table A11: Verification of the relevance of the instrument with a Twitter bot

Dependent variable:	Prayer bot did not tweet (when scheduled)					
	(1)	(2)	(3)	(4)	(5)	(6)
Internet outage	0.042**	0.067***				
	(0.018)	(0.021)				
Lightning strike			0.036*	0.078***		
			(0.021)	(0.026)		
Absence of traffic					0.066**	0.064**
					(0.032)	(0.032)
Year, MoY, DoW FEs	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	1682	1682	1682	1682	1174	1174
Mean dep. var.	0.08	0.08	0.08	0.08	0.09	0.09

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a day. Dependent variable: bot account @IPT_Gaza did not tweet when scheduled over the day. Time period starts on August 3, 2011 when @IPT_Gaza starts tweeting. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths at day t, as well as between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.

Table A12: Social media and the measures of individual emotions of conflict coverage, 2SLS

Outcome variables based on:	Use of emotional words							
Panel A: Negative emotions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable, this panel:	Anger		Fear		Disgust		Sadness	
Log(Conflict tweets)	0.422*	0.142	0.463	0.045	0.270**	0.195	0.336*	0.111
	(0.238)	(0.280)	(0.290)	(0.340)	(0.124)	(0.143)	(0.197)	(0.234)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.484**		0.769***		0.120		0.436**
		(0.207)		(0.269)		(0.093)		(0.177)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.101		0.068		0.242		0.049
		(0.552)		(0.791)		(0.262)		(0.413)
Log(Palestinian deaths+1)	0.104	–3.343**	0.170*	–5.326***	–0.001	–0.867	0.069	–3.038**
	(0.083)	(1.426)	(0.101)	(1.858)	(0.043)	(0.642)	(0.069)	(1.222)
Log(Israeli deaths+1)	0.323**	–0.334	0.304*	–0.155	0.115	–1.591	0.278**	–0.092
	(0.148)	(3.868)	(0.171)	(5.577)	(0.083)	(1.819)	(0.116)	(2.856)
Log(Palestinian deaths+1), t-28 to t-1	–0.030	–0.050	0.023	–0.014	–0.036*	–0.041**	–0.015	–0.039
	(0.039)	(0.038)	(0.046)	(0.046)	(0.020)	(0.018)	(0.032)	(0.031)
Log(Israeli deaths+1), t-28 to t-1	0.114***	0.148***	0.115***	0.166***	0.034**	0.042**	0.081***	0.105***
	(0.032)	(0.046)	(0.039)	(0.057)	(0.016)	(0.021)	(0.026)	(0.037)
Mean dep. var.	2.148	2.096	2.852	2.777	1.020	1.001	2.029	1.987
Panel B: Positive and neutral emotions	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable, this panel:	Joy		Trust		Anticipation		Surprise	
Log(Conflict tweets)	–0.034	–0.254	–0.262	–0.343	–0.043	–0.181	0.154	–0.004
	(0.142)	(0.183)	(0.225)	(0.278)	(0.120)	(0.153)	(0.102)	(0.127)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.407**		0.027		0.223*		0.292***
		(0.166)		(0.247)		(0.125)		(0.097)
Log(Conflict tweets) × Log(Israeli deaths+1)		–0.181		0.542		0.062		–0.061
		(0.328)		(0.471)		(0.262)		(0.212)
Log(Palestinian deaths+1)	0.076	–2.842**	0.201**	–0.062	0.128***	–1.467*	0.070**	–1.984***
	(0.049)	(1.166)	(0.079)	(1.753)	(0.042)	(0.878)	(0.036)	(0.667)
Log(Israeli deaths+1)	0.123*	1.390	0.119	–3.728	0.124*	–0.314	0.099	0.554
	(0.072)	(2.304)	(0.123)	(3.268)	(0.067)	(1.845)	(0.078)	(1.447)
Log(Palestinian deaths+1), t-28 to t-1	0.038	0.020	0.066*	0.057	0.035*	0.026	–0.002	–0.014
	(0.026)	(0.027)	(0.037)	(0.037)	(0.021)	(0.022)	(0.017)	(0.017)
Log(Israeli deaths+1), t-28 to t-1	–0.003	0.018	–0.004	0.034	0.023	0.044**	0.022	0.035
	(0.020)	(0.026)	(0.032)	(0.036)	(0.017)	(0.021)	(0.015)	(0.022)
Mean dep. var.	2.677	2.658	4.930	4.915	2.564	2.540	1.162	1.140
All panels:								
Network-, Year-, MoY-, DoW FEs, Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sample restriction: Days with deaths<15		✓		✓		✓		✓
Observations	4153	3983	4153	3983	4153	3983	4153	3983
F-stat, *Internet outage*	18.22	12.09	18.22	12.09	18.22	12.09	18.22	12.09
F-stat, *Internet outage × Log(PS deaths+1)*		25.19		25.19		25.19		25.19
F-stat, *Internet outage × Log(IL deaths+1)*		13.14		13.14		13.14		13.14

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. "Network-, Year-, MoY-, DoW- FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.

Table A13: Social media and additional topics of conflict news (measured by LDA), 2SLS

	Specification:	1. Direct effect	2. Interactions with casualties			Mean dep. var.
	Coefficients on expl. variables:	Coefficient (SE) on:	Coefficients (SEs) on:			(Prob. of topic)
		log(Conflict tweets)	log(Conflict tweets)	log(Conflict tweets) × log(PS deaths+1)	log(Conflict tweets) × log(IL deaths+1)	
(1)	International law / UN	0.00280	0.00333	-0.00271	0.00940	0.0116
		(0.00714)	(0.00817)	(0.00586)	(0.0134)	
(2)	Family / prison / courts	-0.00868	-0.0167	0.0159	-0.00835	0.0343
		(0.0178)	(0.0234)	(0.0119)	(0.0173)	
(3)	State / peace / negotations	-0.0212	-0.0242	0.00237	-0.0257	0.161
		(0.0351)	(0.0427)	(0.0307)	(0.0830)	
(4)	Police / killing	0.0120	0.0173	-0.00742	0.0399	0.0423
		(0.0241)	(0.0274)	(0.0188)	(0.0465)	
(5)	People / time / US/ right thing	0.0389	0.0595	-0.0389	0.0300	0.125
		(0.0288)	(0.0373)	(0.0280)	(0.0609)	
(6)	Plane crash	0.00175	0.00176	-0.00158	0.00634	0.00730
		(0.00367)	(0.00405)	(0.00304)	(0.00749)	
(7)	Greetings	-0.01000	-0.0212	0.0240	-0.00282	0.0433
		(0.0159)	(0.0201)	(0.0148)	(0.0417)	
(8)	Nuclear weapons / nuclear deal	0.0300	0.0365	-0.0141	0.000107	0.0438
		(0.0254)	(0.0300)	(0.0179)	(0.0338)	
(9)	Border crossing / children	0.00468	0.00502	-0.00368	0.000901	0.00724
		(0.00311)	(0.00361)	(0.00248)	(0.00450)	
(10)	Violence / Israel / Jerusalem	-0.00127	-0.00628	0.0136	-0.00821	0.0219
		(0.0104)	(0.0133)	(0.0133)	(0.0238)	
(11)	Doctor / insurance / medical	-0.00634	-0.00670	0.00357	-0.0168	0.0253
		(0.0113)	(0.0135)	(0.00950)	(0.0184)	
(12)	Economy / market	0.0123	0.0157	-0.00326	-0.0311	0.0404
		(0.0132)	(0.0150)	(0.0117)	(0.0410)	
(13)	Local conditions: water / food	0.0167	0.0209	-0.0109	0.0132	0.0289
		(0.0144)	(0.0177)	(0.0107)	(0.0219)	
(14)	Schools	-0.0119	-0.00544	-0.0143	0.0311	0.0194
		(0.00874)	(0.00790)	(0.0132)	(0.0247)	
(15)	Energy / gulf	0.00113	0.00461	-0.00559	0.00562	0.00819
		(0.00336)	(0.00418)	(0.00454)	(0.00789)	
	Number of observations:	4,153	3,983			
	F-stat, internet outage:	18.22	12.09			
	F-stat, internet outage × log(PS deaths+1):		25.19			
	F-stat, internet outage × log(IL deaths+1):		13.14			

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. Each row presents results of two specifications for the outcome variables listed in the first column. Every regression includes the following controls: fixed effects for each TV network, each calendar year, each month of the year, and each day of the week, the logs of (1+) Palestinian and Israeli deaths at day t, as well as between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity. Table 7 presents the results for those LDA topics, for which we find some significant effects.

B OLS results corresponding to the main 2SLS results

Table B1: OLS on the extent of coverage, corresponding to the 2SLS Table 4

Dependent variable, all panels:	Prime time coverage	Number of stories	Number of keywords	Length in minutes	Length in minutes	Length in minutes
Panel A: Direct effect only	(1)	(2)	(3)	(4)	(5)	(6)
Sample restriction:					Coverage=1	Deaths<15
Log(Conflict tweets)	0.083***	1.155***	37.807***	17.826***	33.127***	14.414***
	(0.015)	(0.198)	(6.896)	(3.166)	(6.396)	(3.022)
Log(Palestinian deaths+1)	0.084***	1.341***	48.710***	22.295***	26.591***	8.713***
	(0.011)	(0.182)	(7.870)	(3.634)	(5.124)	(3.304)
Log(Israeli deaths+1)	0.081**	1.110*	43.128*	20.641*	24.408	20.922*
	(0.035)	(0.589)	(24.445)	(10.785)	(17.231)	(11.047)
News pressure	–0.102***	–1.471***	–49.527***	–24.072***	–42.986**	–21.642***
	(0.028)	(0.379)	(13.628)	(6.618)	(19.059)	(4.803)
Observations	16900	16900	16900	16900	4153	16720
Mean dep. var.	0.101	0.959	23.186	12.833	52.223	10.929
Panel B: Interactions with casualties	(7)	(8)	(9)	(10)	(11)	(12)
Sample restriction:					Coverage=1 & Deaths≤15	Deaths<15
Log(Conflict tweets)	0.057***	0.673***	18.068***	9.010***	20.249***	8.351***
	(0.014)	(0.153)	(4.806)	(2.260)	(4.873)	(2.095)
Log(Conflict tweets) × Log(Palestinian deaths+1)	0.061***	1.132***	45.936***	20.453***	23.174***	19.430***
	(0.007)	(0.128)	(5.752)	(2.570)	(8.697)	(6.418)
Log(Conflict tweets) × Log(Israeli deaths+1)	0.039	0.697	34.105	16.006	26.070*	31.327***
	(0.026)	(0.706)	(31.767)	(13.555)	(15.405)	(12.020)
Log(Palestinian deaths+1)	–0.367***	–7.091***	–293.788***	–130.244***	–154.824***	–124.060***
	(0.051)	(0.848)	(37.590)	(16.777)	(57.547)	(41.107)
Log(Israeli deaths+1)	–0.213	–4.104	–209.368	–97.540	–156.913	–194.364***
	(0.168)	(4.494)	(203.596)	(86.681)	(100.773)	(74.637)
Observations	16900	16900	16900	16900	3983	16720
Mean dep. var.	0.101	0.959	23.186	12.833	45.876	10.929
All panels:						
Network-, Year-, MoY-, DoW- FEs, Controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. The Table presents OLS results corresponding to the 2SLS results presented in Table 4 of the main text.

Table B2: OLS on the emotional intensity, corresponding to the 2SLS Table 5

Outcome variables based on:	Contextual sentiment		Use of emotional words			
Panel A: All and negative emotions	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, this panel:	Negative contextual sentiment		Negative emotions mean		All emotions mean	
Log(Conflict tweets)	1.843***	1.759***	0.258***	0.257***	0.166***	0.157***
	(0.333)	(0.377)	(0.049)	(0.055)	(0.030)	(0.033)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.123		–0.012		0.011
		(0.244)		(0.039)		(0.026)
Log(Conflict tweets) × Log(Israeli deaths+1)		1.406*		0.203*		0.124**
		(0.730)		(0.115)		(0.062)
Log(Palestinian deaths+1)	0.668***	–0.326	0.123***	0.200	0.084***	–0.006
	(0.194)	(1.764)	(0.031)	(0.280)	(0.019)	(0.180)
Log(Israeli deaths+1)	1.343**	–8.186	0.274**	–1.059	0.151**	–0.678
	(0.633)	(5.122)	(0.121)	(0.788)	(0.068)	(0.422)
Log(Palestinian deaths+1), t-28 to t-1	0.019	–0.024	0.000	–0.005	0.008	0.003
	(0.113)	(0.113)	(0.018)	(0.018)	(0.011)	(0.012)
Log(Israeli deaths+1), t-28 to t-1	0.528***	0.637***	0.088***	0.106***	0.034**	0.047***
	(0.163)	(0.179)	(0.027)	(0.030)	(0.016)	(0.018)
Mean dep. var.	15.878	15.592	2.012	1.965	2.560	2.531
Panel B: Neutral and positive emotions	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable, this panel:	Positive contextual sentiment		Positive emotions mean		Neutral emotions mean	
Log(Conflict tweets)	0.011	–0.214	0.094***	0.078**	0.145***	0.137***
	(0.196)	(0.212)	(0.030)	(0.033)	(0.025)	(0.028)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.507***		0.037		0.009
		(0.186)		(0.029)		(0.023)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.346		0.073		0.097*
		(0.585)		(0.061)		(0.050)
Log(Palestinian deaths+1)	0.413***	–3.657***	0.059***	–0.239	0.070***	0.020
	(0.149)	(1.364)	(0.022)	(0.205)	(0.016)	(0.164)
Log(Israeli deaths+1)	0.365	–2.201	0.081	–0.426	0.097*	–0.551
	(0.470)	(4.205)	(0.076)	(0.426)	(0.054)	(0.348)
Log(Palestinian deaths+1), t-28 to t-1	0.200*	0.122	0.020	0.011	0.005	0.003
	(0.107)	(0.113)	(0.016)	(0.016)	(0.010)	(0.010)
Log(Israeli deaths+1), t-28 to t-1	–0.037	0.041	–0.008	0.005	0.021	0.028**
	(0.150)	(0.166)	(0.021)	(0.023)	(0.013)	(0.014)
Mean dep. var.	19.643	19.572	3.804	3.787	1.863	1.840
All panels:						
Network-, Year-, MoY-, DoW FEs, Controls	✓	✓	✓	✓	✓	✓
Sample restriction: Days with deaths<15		✓		✓		✓
Observations	4153	3983	4153	3983	4153	3983

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. The Table presents OLS results corresponding to the 2SLS results presented in Table 5 of the main text.

Table B3: OLS on topics measured by keywords, corresponding to the 2SLS Table 6

Panel A: Mentions of civilians	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable, this panel:	The number of keywords on the following topic divided by the total number of words:							
	People*		Children and teenagers*		Civilian casualties*		Terror*	
Log(Conflict tweets)	0.002 (0.008)	–0.010 (0.009)	–0.000 (0.002)	0.001 (0.003)	0.002*** (0.001)	0.001 (0.001)	–0.001 (0.005)	–0.002 (0.005)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.017** (0.007)		–0.003 (0.002)		0.001*** (0.000)		–0.002 (0.005)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.042** (0.019)		–0.005 (0.007)		0.005*** (0.001)		0.009 (0.011)
Log(Palestinian deaths+1)	0.016*** (0.006)	–0.115** (0.054)	–0.000 (0.002)	0.021 (0.016)	0.003*** (0.001)	–0.009*** (0.003)	0.001 (0.003)	0.014 (0.036)
Log(Israeli deaths+1)	–0.002 (0.016)	–0.290** (0.138)	0.005 (0.005)	0.044 (0.052)	0.002 (0.002)	–0.029*** (0.011)	0.014 (0.011)	–0.043 (0.077)
Mean dep. var.	0.330	0.327	0.030	0.029	0.004	0.003	0.067	0.067
Panel B: Mentions of officials	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable, this panel:	The number of keywords on the following topic divided by the total number of words:							
	Hamas*		IL and PS leaders*		US foreign policy off.*		Elections*	
Log(Conflict tweets)	0.048*** (0.010)	0.031*** (0.009)	0.012** (0.006)	0.013** (0.006)	–0.019*** (0.006)	–0.021*** (0.006)	–0.005 (0.007)	–0.002 (0.008)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.034*** (0.008)		–0.001 (0.005)		–0.001 (0.004)		–0.002 (0.005)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.017 (0.024)		0.006 (0.016)		0.020* (0.011)		–0.005 (0.009)
Log(Palestinian deaths+1)	0.023*** (0.006)	–0.240*** (0.051)	–0.001 (0.004)	–0.005 (0.039)	0.005 (0.005)	0.010 (0.031)	–0.007 (0.004)	0.009 (0.036)
Log(Israeli deaths+1)	0.001 (0.014)	–0.123 (0.173)	–0.020* (0.011)	–0.072 (0.118)	–0.000 (0.012)	–0.154* (0.080)	–0.008 (0.008)	0.026 (0.065)
Mean dep. var.	0.085	0.074	0.102	0.104	0.070	0.069	0.088	0.091
Panel C: Mentions of social media	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Dependent variable, this panel:	The dummy indicating a mention of the following social media:							
	Twitter		Facebook		YouTube		"Social media"	
Log(Conflict tweets)	0.064*** (0.013)	0.035*** (0.012)	0.015 (0.018)	0.006 (0.019)	0.033*** (0.010)	0.021** (0.009)	0.019* (0.011)	0.007 (0.011)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.047*** (0.016)		0.019 (0.020)		0.023** (0.011)		0.030** (0.013)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.089* (0.048)		0.056 (0.060)		0.015 (0.033)		0.101*** (0.031)
Log(Palestinian deaths+1)	0.055*** (0.013)	–0.323*** (0.112)	0.075*** (0.015)	–0.084 (0.136)	0.016* (0.008)	–0.148* (0.078)	0.052*** (0.011)	–0.189** (0.089)
Log(Israeli deaths+1)	0.019 (0.041)	–0.576* (0.347)	0.008 (0.039)	–0.375 (0.405)	–0.030 (0.022)	–0.119 (0.228)	0.051 (0.035)	–0.652*** (0.218)
Mean dep. var.	0.129	0.113	0.149	0.136	0.050	0.046	0.088	0.075
All panels:								
TV Network, Year, MoY, DoW FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sample: Days with < 15 deaths		✓		✓		✓		
Observations	4153	3983	4153	3983	4153	3983	4153	3983

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. "US foreign policy off." stands for US foreign policy officials. The Table presents OLS results corresponding to the 2SLS results presented in Table 6 of the main text.

Table B4: OLS on topics measured by measured by LDA, corresponding to the 2SLS Table 7

Specification:	1. Direct effect	2. Interactions with casualties			Mean dep. var.
Coefficients on explanatory variables:	Coefficient (SE) on:	Coefficients (SEs) on:			(Prob. of topic)
	log(Conflict tweets)	log(Conflict tweets)	log(Conflict tweets) × log(PS deaths+1)	log(Conflict tweets) × log(IL deaths+1)	
Outcome variable (LDA topic):					
(1) TERRORISM: terrorist / group / kill / Hamas	0.00404***	0.00366**	6.74e-05	0.00497*	0.0146
	(0.00136)	(0.00148)	(0.00126)	(0.00254)	
(2) IL LEADERSHIP: prime minister / Netanyahu	0.00210	0.00152	0.00184	0.00101	0.0370
	(0.00205)	(0.00219)	(0.00191)	(0.00440)	
(3) ELECTIONS: politics / elections / vote / people	-0.0181***	-0.0186***	-7.10e-05	0.00518	0.0466
	(0.00372)	(0.00411)	(0.00256)	(0.00492)	
(4) SETTLEMENTS: settlements / [west] bank / construct	-0.00272*	-0.00156	-0.00314	-0.00398	0.0234
	(0.00153)	(0.00174)	(0.00248)	(0.00828)	
(5) US FOREIGN POLICY: secretary of state / report / Kerry	0.00129	0.00216	-0.000880	0.00405	0.0569
	(0.00296)	(0.00315)	(0.00338)	(0.0124)	
(6) OBAMA: president Obama / white house	-0.00562	-0.00632	0.00247	-0.00932	0.0825
	(0.00365)	(0.00395)	(0.00375)	(0.0107)	
(7) ATTACKS [1]: air strike / fire / rocket / people	0.0213***	0.0109***	0.0181***	0.00400	0.0225
	(0.00367)	(0.00293)	(0.00336)	(0.0131)	
(8) ATTACKS [2]: report / people / attack / kill / government	0.00462	0.00769**	-0.00682**	0.00412	0.0688
	(0.00338)	(0.00382)	(0.00309)	(0.00889)	
(9) ATTACKS [3]: Hamas / rocket / civilian / iron dome	0.00836***	0.00277*	0.00496**	0.0130**	0.0109
	(0.00203)	(0.00146)	(0.00211)	(0.00563)	
(10) ATTACKS [4]: tunnel / Hamas / fire / soldier / people	0.00521**	0.00526**	0.00739**	-0.00866	0.0161
	(0.00214)	(0.00223)	(0.00287)	(0.00890)	
(11) All topics on ATTACKS together: [1]+[2]+[3]+[4]	0.0395***	0.0266***	0.0236***	0.0125	0.118
	(0.00738)	(0.00687)	(0.00617)	(0.0252)	
All regressions with this specification:					
Number of observations:	4,153		3,983		

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. Each row presents results of two specifications for the outcome variables listed in the first column. The Table presents OLS results corresponding to the 2SLS results presented in Table 7 of the main text.

Table B5: OLS on details and similarity, corresponding to the 2SLS Table 8

Panel A: Mentions of details	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, this panel:	Share of keywords on heavy ammunition* in total words		Dummy for mentions of concrete small geographic locations in: Israel		Palestinian Territor.	
Log(Conflict tweets)	0.074***	0.041***	0.044**	0.019	0.022	0.015
	(0.014)	(0.012)	(0.019)	(0.020)	(0.015)	(0.015)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.053***		0.027		0.036*
		(0.013)		(0.021)		(0.020)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.031		0.128***		–0.030
		(0.027)		(0.048)		(0.047)
Log(Palestinian deaths+1)	0.069***	–0.328***	0.052***	–0.144	0.047***	–0.222
	(0.010)	(0.090)	(0.015)	(0.144)	(0.013)	(0.138)
Log(Israeli deaths+1)	0.004	–0.206	0.115***	–0.798**	0.073*	0.265
	(0.025)	(0.185)	(0.044)	(0.335)	(0.039)	(0.331)
Sample: Days with < 15 deaths		✓		✓		✓
Mean dep. var.	0.450	0.440	0.381	0.381	0.385	0.385
Observations	3466	3296	1551	1551	908	908
Panel B: Similarity across networks	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable, this panel:	Similarity of conflict-related stories by US TV networks to:					
	other US TV networks		to Al Jazeera		to Al Jazeera	
Sample, US TV networks considered:	All		All		CNN, FOX, and PBS	
Log(Conflict tweets)	0.054***	0.040***	0.042***	0.040***	0.051***	0.052***
	(0.012)	(0.013)	(0.011)	(0.012)	(0.012)	(0.013)
Log(Conflict tweets) × Log(Palestinian deaths+1)		0.025***		0.003		–0.001
		(0.009)		(0.006)		(0.006)
Log(Conflict tweets) × Log(Israeli deaths+1)		0.053***		–0.026		–0.015
		(0.016)		(0.016)		(0.013)
Log(Palestinian deaths+1)	0.026***	–0.171***	0.024***	0.004	0.024***	0.034
	(0.007)	(0.066)	(0.005)	(0.045)	(0.005)	(0.045)
Log(Israeli deaths+1)	0.022	–0.342***	0.013	0.214	0.031*	0.146
	(0.018)	(0.117)	(0.019)	(0.131)	(0.016)	(0.107)
Sample: Days with < 15 deaths		✓				
Mean dep. var.	0.450	0.440	0.381	0.381	0.385	0.385
Observations	3466	3296	1551	1551	908	908
All panels:						
TV Network, Year, MoY, DoW FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. The Table presents OLS results corresponding to the 2SLS results presented in Table 8 of the main text.

C The results of the robustness exercises described in detail

In this section, we present the results of a battery of robustness checks.

C.1 Robustness of the direct effect of conflict tweets

The first set of robustness exercises focuses on the direct effect of social media in Israel and Palestine (measured by tweets) on TV news coverage of the conflict in the US, i.e., Equation 1. For conciseness, we focus on the four main outcomes: the length of the daily conflict-related news to test for the robustness of the results for the extent of coverage, the score of the negative contextual sentiment of the conflict-related news to test for the robustness of the results for the emotional intensity, and the number of words associated with the topics on people, civilians, children, babies and teenagers and with the topics on US foreign policy officials and elections (as in the baseline divided by the total number of words in the conflict-related news).

We organize the presentation of the results of the eleven robustness exercises in a graphical form separately for each outcome of interest, such that we first present the coefficient of interest, i.e., the coefficient on the log conflict tweets from the 2SLS baseline estimation with the 90% confidence interval, and then present the eleven corresponding coefficients (again, with their confidence intervals) for each robustness check right below the baseline result. For each robustness exercise, we also report the F-statistic for the excluded instrument in the first stage.

The robustness of the direct effect of tweets on the length of the daily conflict-related news is presented on Figure C1, on the score of the negative contextual sentiment on Figure C2, on the topic associated with civilians and children on Figure C3, and on the topics associated with US foreign policy officials and elections on Figure C4. These figures are presented below in this section of the Online Appendix.

Let us now describe the eleven robustness check in order of appearance in Figures C1 to C4.

1. First, we verify that our results are robust to considering the dummy for lightning strikes only as the instrument for conflict-one social media activity. The results are presented on the figures right below the baseline. The F-statistic from the first stage is lower than when we consider both sources of internet outages, but it is still strong enough not to worry about the weakness of the instrument. The second-stage results are significant in all specifications and have the expected sign. The point estimates of the second-stage coefficient of interest are larger in magnitude than the baseline for the length and the topic related to civilians and are comparable for the other two outcomes. The difference in the magnitude of could be explained by the difference in compliers for the two instruments. To be affected by lightning strikes users need to have no power surge protection tools.

2. In the next robustness check, we use an alternative definition of conflict tweets. In particular, we consider as conflict-related the tweets for which the the Naive-Bayes classifier algorithm deems that it is 75% likely that this tweet is conflict related. In the baseline, we use the 50% threshold. On the figures, we refer to this robustness check as "more conservative measure of conflict tweets." The results are practically identical to the baseline.

3. Nest, we use all tweets with keywords from the conflict zone instead of the conflict-related tweets; and again the results are completely robust.

4. In the baseline, we define a TV news story to be conflict-related if it mentions "Israel" and "Palestin" or "Israel" and "Gaza" at least five times within the news segment. We show robustness to using all news segments, which mention "Israel" and "Palestin" or "Israel" and "Gaza" at least once. The results are unchanged.

5. We add local temperature in the conflict zone to the list of baseline controls; this does not change anything.

6. We also verify that using the inverse hyperbolic sine transformation, IHS(Casualties), instead of taking the log(Casualties+1) for the number of Israeli and Palestinian casualties also does not change the estimates.
7. The results also do not change when we include in the sample the thirteen days of the most intense fighting during the 2014 Gaza War. (These days are excluded from the baseline because they constitute an outlier in terms of the number of casualties.)
8. We also verify that the results do not change if in addition to including the thirteen days of the most intense fighting during the 2014 Gaza War, we winsorize the number of casualties during these days.
9. As a next robustness check, we exclude from the sample all the days with less than fifteen deaths. Again, the results are fully robust.
10. As a baseline, we adjust standard errors for clusters in the error term at a day level, recognizing that our main explanatory variable is measured daily. To ensure that the results are robust to alternative assumptions about variance-covariance matrix, we use re-calculate standard errors under the assumption that, in addition to correlation between different TV networks, there is also a serial correlation over a moving time window, so that the error terms today are also correlated with error terms yesterday and tomorrow. The results are robust. It is also worth noting that the first stage is string enough in this specification.
11. We also tried to enlarge the window in which we allow the error terms to be correlated. The last robustness check reports results with clusters within $+/-3$ days around day t. The results of the second stage remain significant in this specification, but the F-statistic from the first stage falls below the conventional level.

Figure C1: Robustness: Direct effect, the length of US conflict news

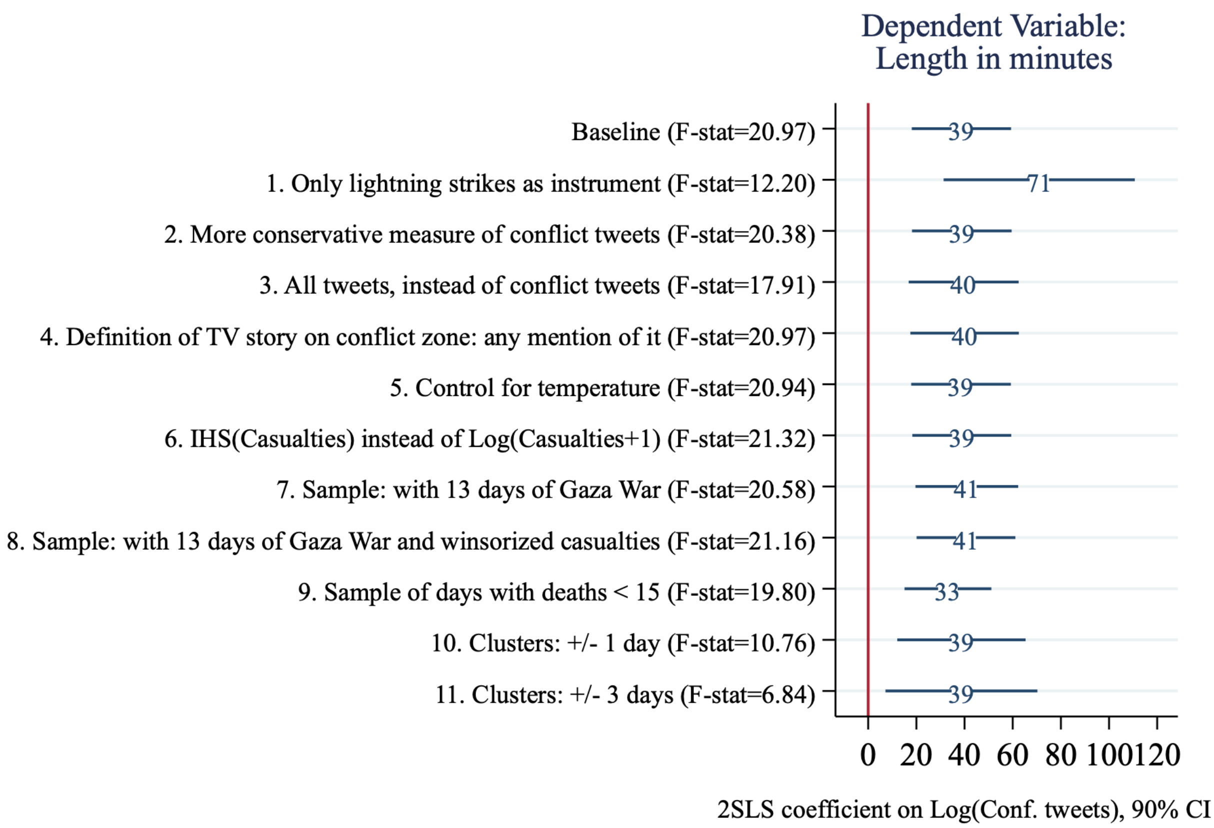


Figure C2: Robustness: Direct effect, negative emotions

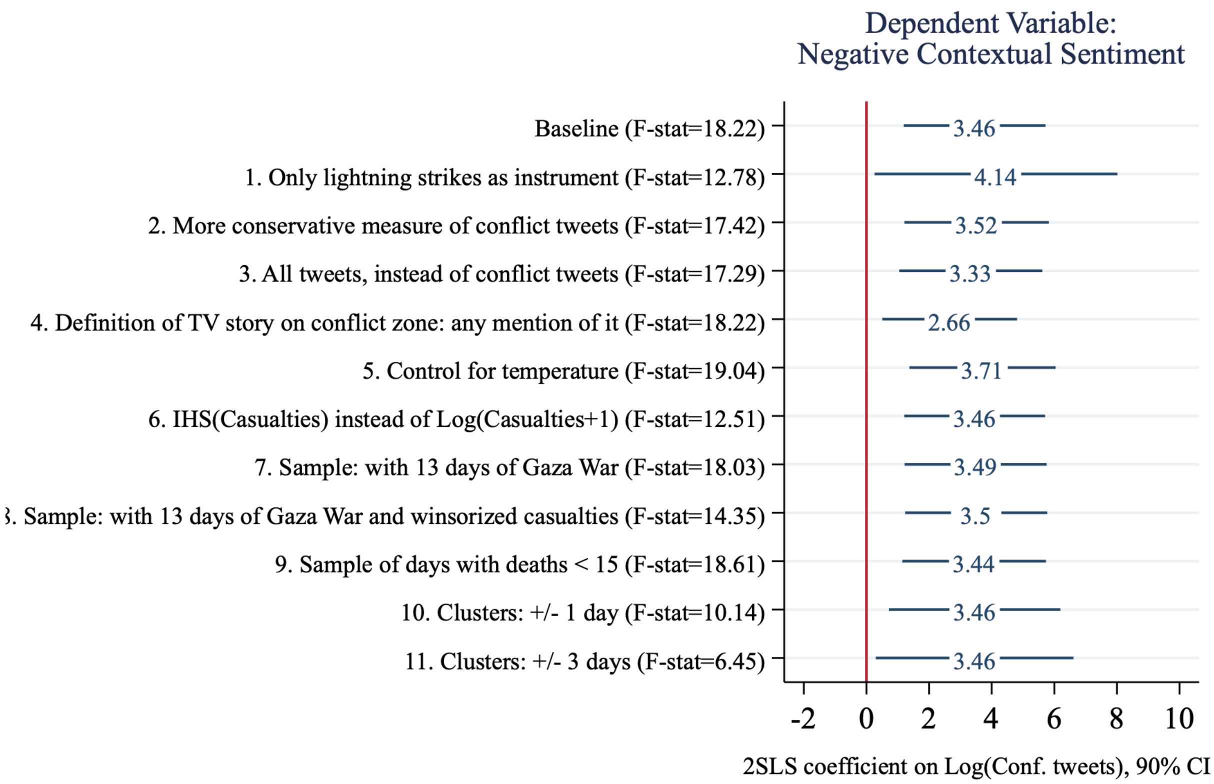


Figure C3: Robustness: Direct effect, Topics about civilians*

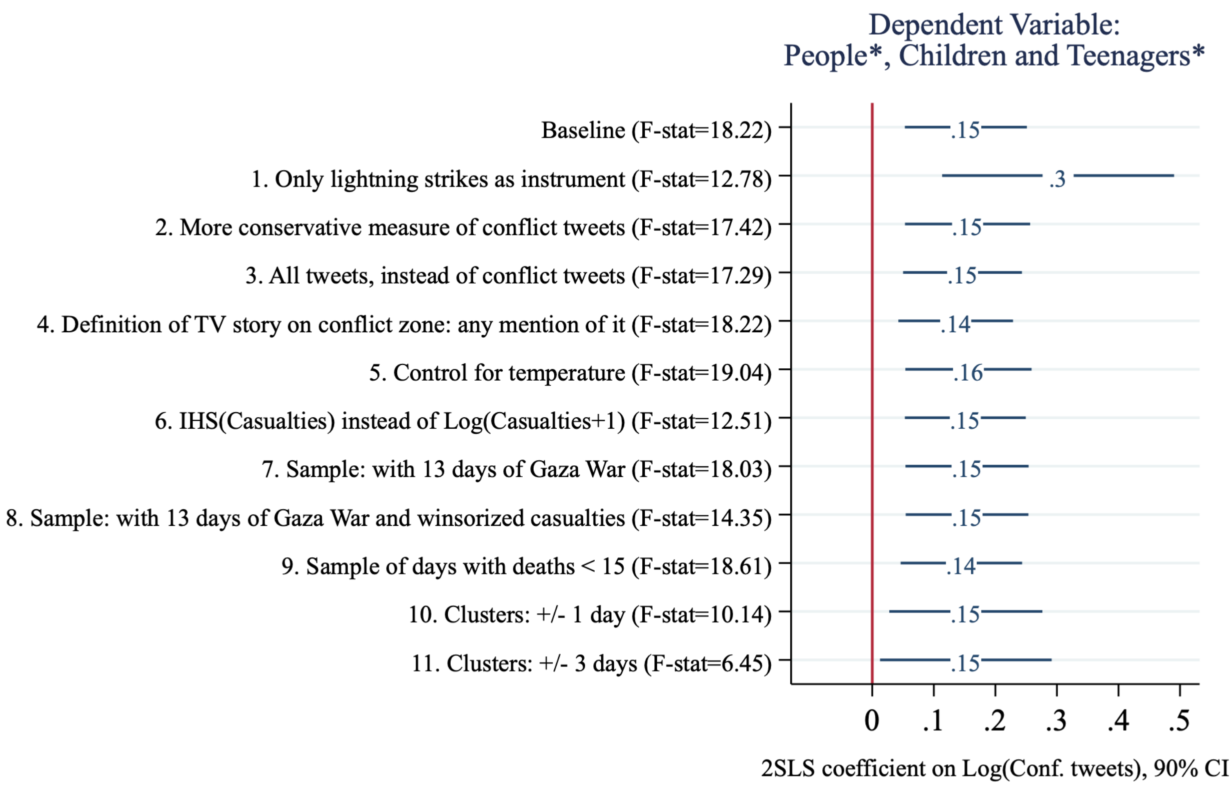
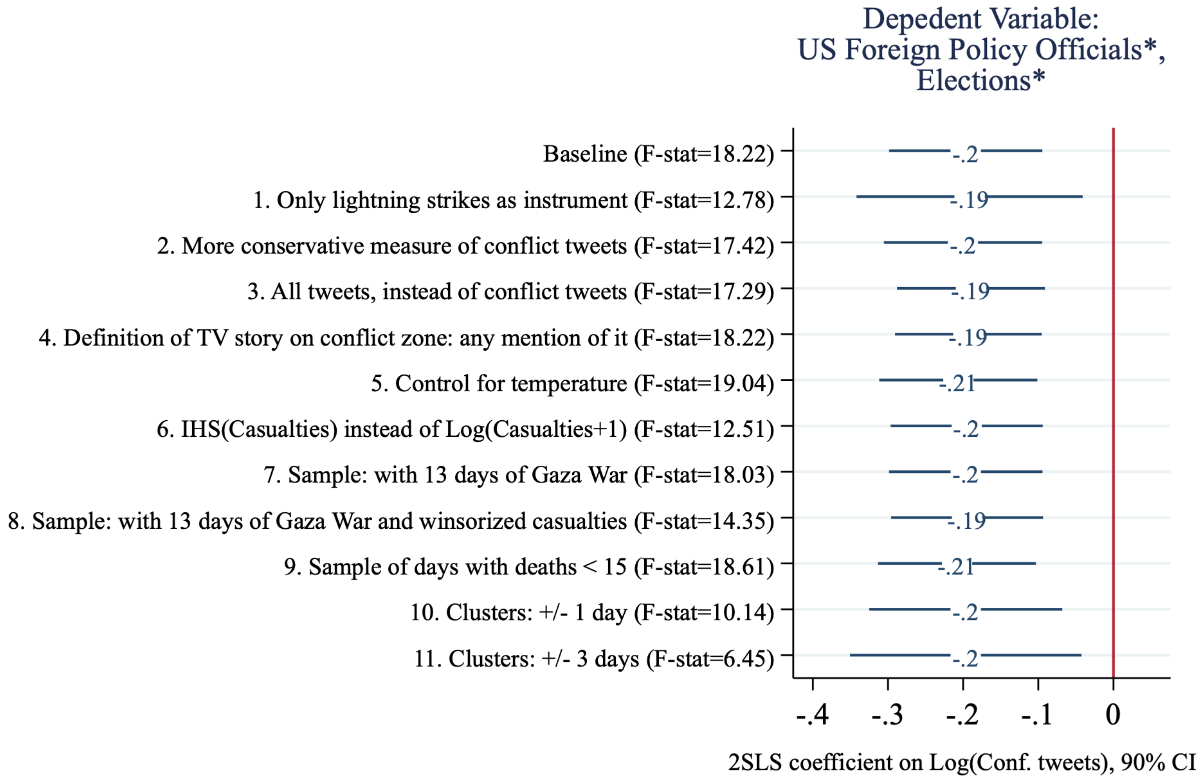


Figure C4: Robustness: Direct effect, Topics about US foreign policy officials* and elections*



C.2 Robustness of the effect of conflict tweets interacted with casualties on the two sides of the conflict

As shown in the main text of the paper, negative emotions and mentions of civilian casualties increase in the US conflict-related news when social media in the conflict zone is not muted due to internet outages and there are Palestinian casualties. We present robustness of these results focusing on the two outcome measures: negative contextual sentiment and the mentions "civilian casualties" divided by the total number of words in conflict-zone-related news.

In the baseline specification, we operationalize this by interacting log conflict tweets with casualties on both sides of the conflict. We use the same strategy for all, but one of the robustness checks listed above. If we use lightning strikes as the only instrument, we cannot identify three endogenous variables in the subsample of days conditional on conflict coverage because the first stage is too weak in this case. As an alternative to the specification that we use as a baseline, we restrict the sample further to days with Palestinian casualties and estimate the direct effect of conflict tweets. This is a less demanding specification, but it tests the same hypothesis: what is the effect of conflict tweets on the days with Palestinian casualties. The first stage is somewhat weak irrespective of whether we use lightning strikes or both sources of internet outages as the instrument: F-statistics are equal to 6.56 and 7.46, respectively. So, we use the Anderson-Rubin confidence sets corrected for the weak instruments problem in the second stage. The results of this robustness exercise are presented in Figure C5 (found below in this section of the Online Appendix). We report the results of this more parsimonious specification with using both sources of internet outages and lightning strikes only as alternative instruments. The results are fully robust robust for the negative contextual sentiment. For mentions of civilian casualties, the effect is actually stronger with only lightning strikes as the instrument. (The effect is marginally insignificant with both sources of internet outage as instrument in this specification, when we use adjustment to weak instruments, whereas it is highly significant with lightning strikes only.) Overall, we conclude that the results are broadly robust to using lightning strikes only.

For all the other nine robustness exercises, we use the same specification as in the baseline.

Note that the sample in the baseline for this specification is days below 15 deaths (thus, there is one less robustness than for the direct effect). The estimated coefficients from the second-stage and F-statistics from the first stage are presented in Figure C6 for the outcome of the negative contextual sentiment of the conflict-related news and in Figure C7 for the mentions of civilian casualties. As above, we present the baseline coefficients first and the result of each robustness exercise right below it. We use the same numbering of the robustness exercises as in Section C.1 of this Online Appendix. Overall, the results are robust.

Figure C5: Robustness to using lightning strikes only as instrument.
More parsimonious specification than with interactions:
Direct effect of tweets on days with Palestinian casualties

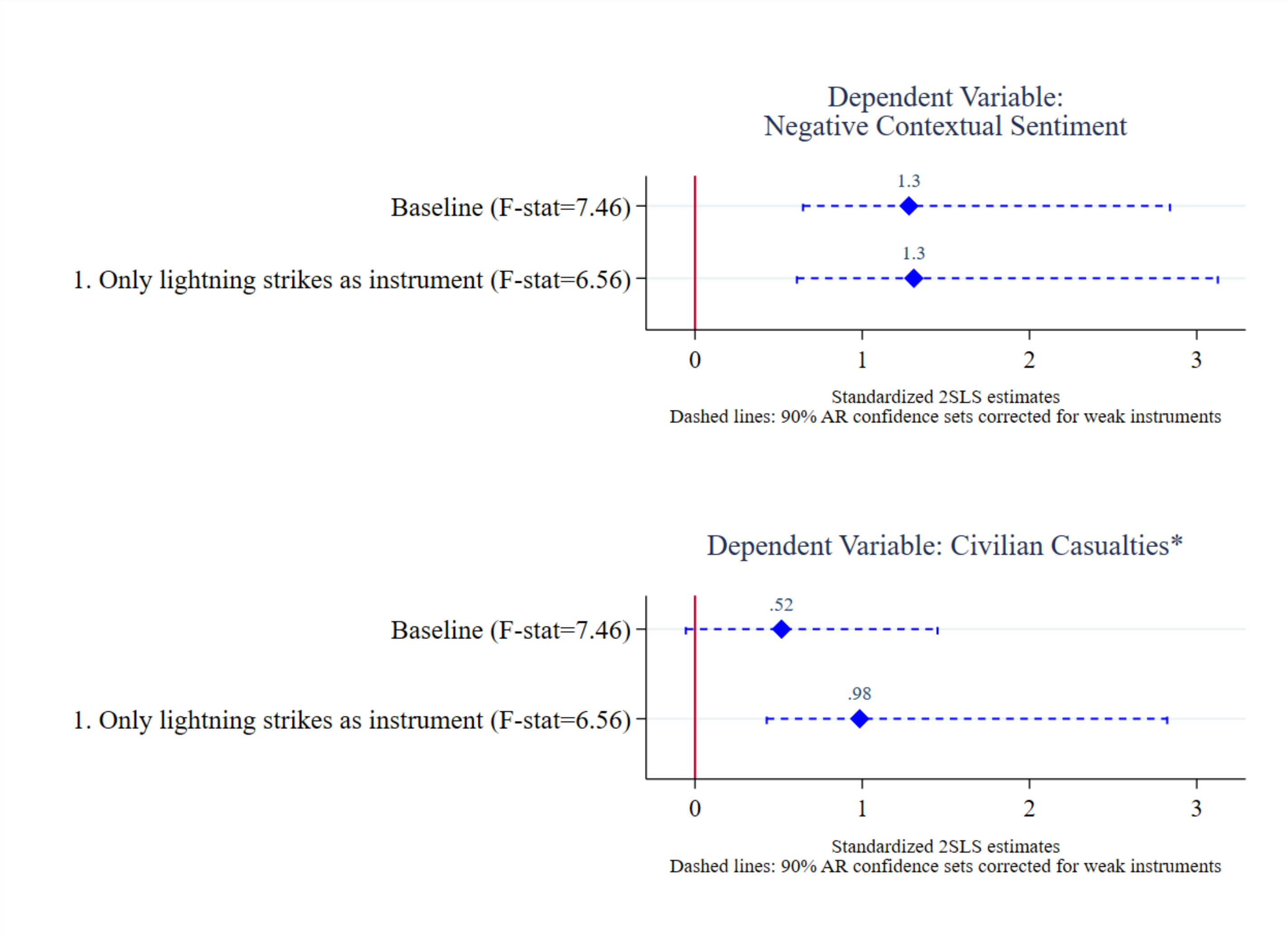


Figure C6: Robustness: The effect of conflict tweets interacted with casualties on negative contextual sentiment

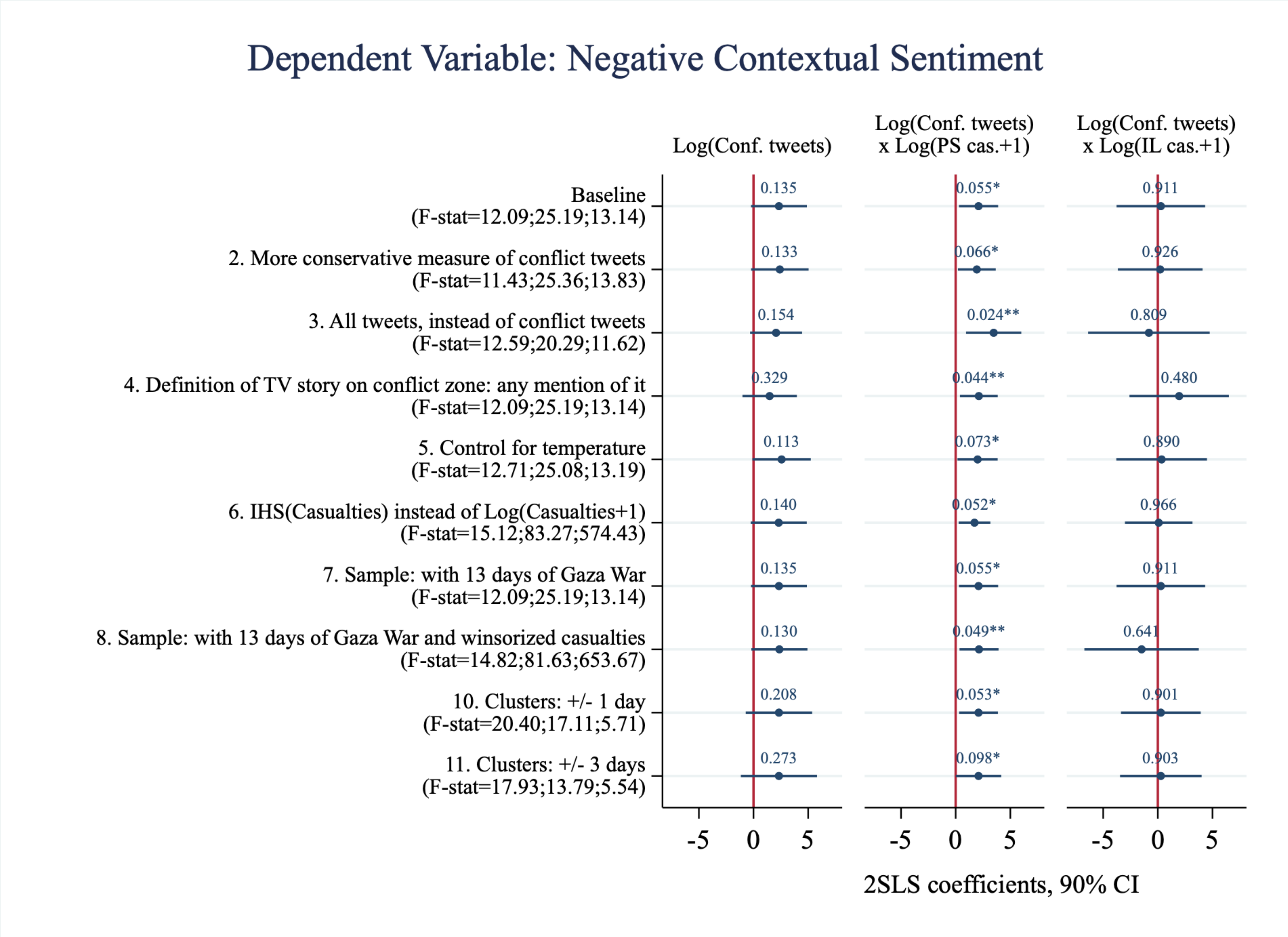
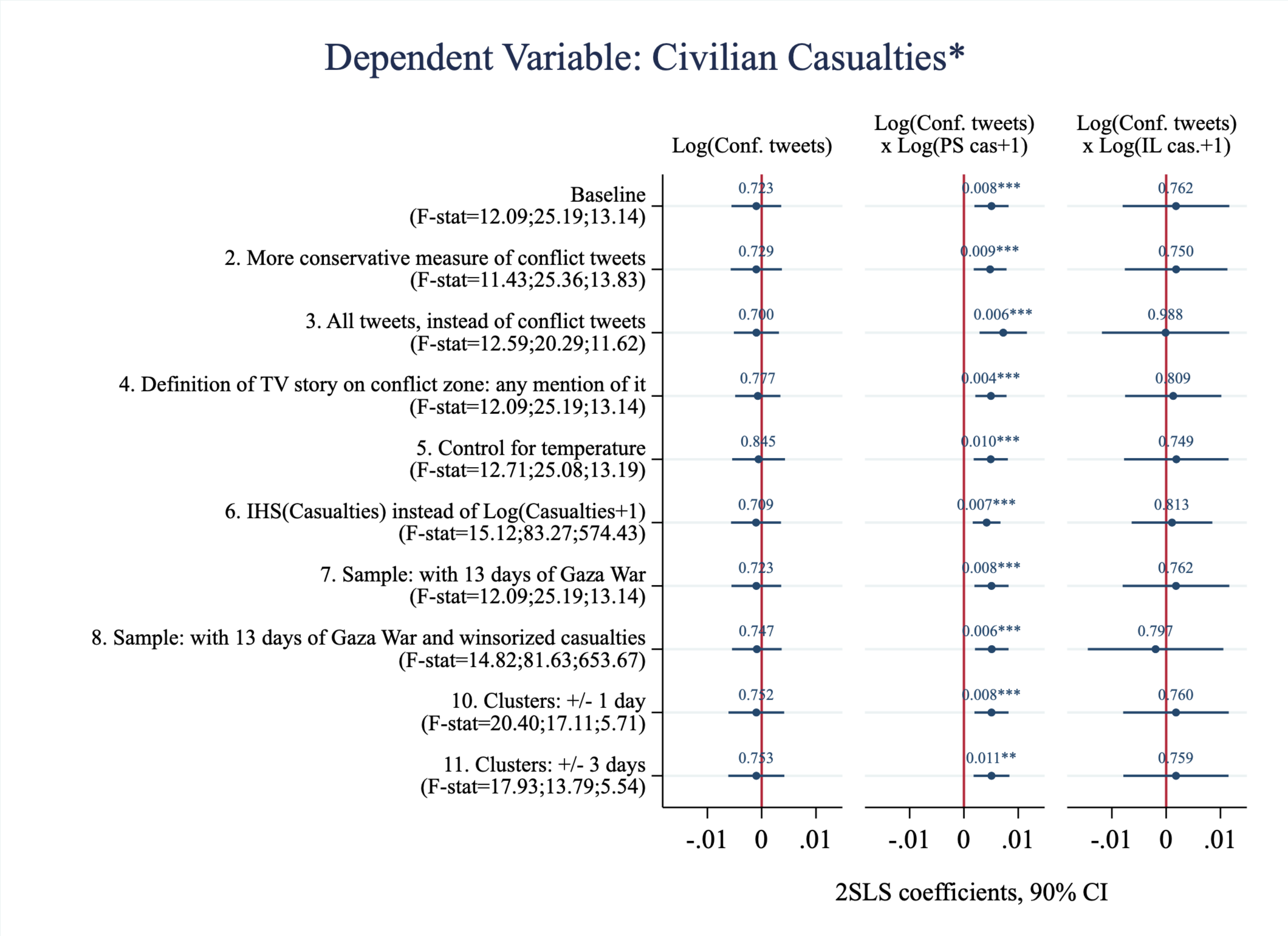


Figure C7: Robustness: The effect of conflict tweets interacted with casualties on civilian casualties



C.3 Robustness of the extent-of-coverage results to using Vanderbilt TV News Archive data

In Table C1 (presented below), we report robustness to using the measures of the extent of conflict coverage by US TV from the alternative source of data, the Vanderbilt TV News Archive. In particular, we built the following two measures from these data: the prime time coverage dummy and the length of prime-time conflict-related news. These data cover only the evening (i.e., prime-time) news for four US TV networks: ABC, CBS, CNN, and NBC. As this data source does not have transcripts, we can only use to study the effect on the extent of coverage. The results are robust.

Table C1: Robustness: Social media in the conflict zone and the extent of conflict coverage measured with Vanderbilt TV News Archive, 2SLS

Dependent variable, all panels:	Prime time coverage	Prime time coverage	Length in minutes	Length in minutes
Panel A: Direct effect only	(1)	(2)	(3)	(4)
Sample restriction:	None	Deaths<15	None	Deaths<15
Log(Conflict tweets)	0.086**	0.060*	0.562**	0.259**
	(0.035)	(0.032)	(0.253)	(0.103)
Log(Palestinian deaths+1)	0.047***	0.023*	0.298***	0.100*
	(0.013)	(0.012)	(0.099)	(0.058)
Log(Israeli deaths+1)	0.049*	0.041	0.375	0.138
	(0.028)	(0.028)	(0.294)	(0.178)
News pressure	–0.038**	–0.026*	–0.383**	–0.126**
	(0.018)	(0.015)	(0.152)	(0.056)
Observations	9176	9084	9176	9084
Mean dep. var.	0.019	0.014	0.072	0.039
F-stat, *Internet outage*	20.66	19.64	20.66	19.64
Panel B: Interactions with casualties	(5)	(6)	(7)	(8)
Sample restriction:	None	Deaths<15	None	Deaths<15
Log(Conflict tweets)	0.027	0.021	0.072	0.045
	(0.035)	(0.036)	(0.192)	(0.099)
Log(Conflict tweets) × Log(Palestinian deaths+1)	0.081***	0.095**	0.651**	0.509**
	(0.031)	(0.047)	(0.327)	(0.223)
Log(Conflict tweets) × Log(Israeli deaths+1)	–0.014	–0.020	0.083	–0.015
	(0.055)	(0.068)	(0.381)	(0.235)
Log(Palestinian deaths+1)	–0.545**	–0.620**	–4.450*	–3.328**
	(0.227)	(0.310)	(2.355)	(1.472)
Log(Israeli deaths+1)	0.126	0.160	–0.368	0.142
	(0.379)	(0.457)	(2.441)	(1.487)
Observations	9176	9084	9176	9084
Mean dep. var.	0.019	0.014	0.072	0.039
F-stat, *Internet outage*	14.42	13.04	14.42	13.04
F-stat, *Internet outage × Log(PS deaths +1)*	9.47	15.39	9.47	15.39
F-stat, *Internet outage × Log(IL deaths +1)*	19.19	11.78	19.19	11.78
All panels:				
Network-, Year-, MoY-, DoW- FEs, Controls	✓	✓	✓	✓

Note: *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is date × TV network. Standard errors clustered at date level in parentheses. All Panels have the same dependent variables and these variables are measured on Vanderbilt TV News Archive data. Length is measured on prime time news only, since Vanderbilt TV News Archive does not record information for other news programs. "Network-, Year-, MoY-, DoW- FEs" denote fixed effects for each TV network, each calendar year, each month of the year, and each day of the week. "Controls" stand for the logs of (1+) Palestinian and Israeli deaths between $t-28$ and $t-1$, news pressure, dummy for other conflicts involving Israel, and rain and wind intensity.