Supplementary Information: Does Social Media Influence Conflict? Evidence from the 2012 Gaza Conflict*

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A.1 Data Sources and Coding

To understand how international public support and international mediators influenced the 2012 Gaza Conflict, I create 9 variables that track key aspects of the conflict. Each variable is coded at the hourly level across the 179 hours of the conflict. The variables capture the attention of the mediators, actions and communication of the conflict participants, and levels of public support. The 9 variables and their associated names (italicized within the parentheses) are given below.

- Hamas Conflict Intensity (*H2I*)
- Israel Conflict Intensity (*I2H*)
- *@IDFSpokesperson* Aggressiveness (*IDF*)
- *@AlQassamBrigade* Aggressiveness (*AQB*)

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- UN Attention (*UN*)
- Egypt Attention (*Egypt*)
- US Attention (*US*)
- #GazaUnderAttack Mentions (*#Gaza*)
- #IsraelUnderFire Mentions (*#Israel*)

The international interest in the Israeli-Palestinian conflict lead to multiple, competing news organizations covering the 2012 Gaza Conflict (Calderone 2012). Increased media coverage provides better density for creation of a conflict events database (Gerner, Schrodt, Francisco and Weddle 1994). However, having multiple media sources with their own biases and slant presents researchers with unique difficulties (Almeida and Lichbach 2003; Reeves, Shellman and Stewart 2006; Davenport 2009). Particularly in the case of the Israeli-Palestinian conflict, researchers must be cognizant of the bias and slant of particular sources (Zeitzoff 2011).

To construct a conflict events database of Israeli and Hamas conflict intensity towards each other, as well as US, Egyptian, and UN attention to the conflict, I drew upon two sources. I used Al Jazeera's *Gaza Crisis: Gaza Live Blog* (Al Jazeera 2012) and Haaretz's *Live Blog: Israel-Gaza Conflict 2012* (Haaretz 2012). Both of the live blogs reported on the conflict at frequent intervals (usually every 10 or 15 minutes). They also reported statements and actions by international mediators and leaders. Each post generally contained an actor or actors, an action and was timestamped. To create a conflict intensity score for Israel and Hamas towards each other, I coded each relevant blog post from Al Jazeera (2012) and Haaretz (2012) following the coding scheme in Table 1. The conflict intensity scores were aggregated at the hourly level. The conflict intensity should be interpreted as a general measure of how aggressive Hamas and Israeli actions were towards each other in a given period in line with other events data coding scheme (Azar 1980; Schrodt 1994).[1]

[1] Implicit in the hourly-level aggregation and coding scheme from Table 1 is the fact that two incidents of verbal conflict are equivalent to one incident of material conflict. A concern may be that the aggregation choices mask conflict dynamics. However, the scale used is reduced in complexity compared to other event scales (Goldstein and Freeman 1990), so there is less threat

For instance if in an hour time period Hamas threatened Israel and launched rockets, Hamas's conflict intensity would be coded as a 3 (1+2). Or, if in an hour time period Israel called up reserve troops and completed two separate air strikes that would be coded as a 5 for Israel's conflict intensity (1+2+2).

It is important to highlight the fact that Haaretz and Al Jazeera covered the conflict from different geographic bases and with different audiences in mind. Al Jazeera had more reporters in Gaza than Haaretz, whose focus was on Israel (Al Jazeera 2012; Haaretz 2012). Furthermore, each source was playing to a different audiences. Al Jazeera's audience demographics tend to be a mix of Arab, left-leaning, and mostly pro-Palestinian individuals.[2] Conversely, Haaretz is traditionally considered a liberal Israeli newspaper.[3] Their coverage and scope of events differed to match their audience demographics and reporting locations. To create a more accurate database of the conflict I combined Haaretz and Al Jazeera conflict intensity scores for both Hamas and Israel to create a unified conflict score for both Hamas and Israel.[4]

Score	**Description**	**Example**
2	Material Conflict	Use of rockets, artillery shells, airstrikes, bombings; military engagement.
1	Verbal Conflict	Threats; warnings; calling up of reserve troops; denigrating the other side.

Table 1: **Israel and Hamas Conflict Intensity Scores**

I also used the Al Jazeera and Haaretz live blogs to develop a measure of international attention to the conflict for each of the mediators involved.[5] For the US, Egypt and the UN, I coded

from aggregation. Furthermore, in Section 5.3 I show that the main results do not change if I separate out verbal conflict and material conflict. For a more complete take on aggregation and scale issues in event data see Schrodt, Yonamine and Bagozzi (2013).

[2]See here for an overview of their demographics `http://www.allied-media.com/aljazeera/al_jazeera_viewers_demographics.html`

[3]For instance see `http://ajr.org/Article.asp?id=5077`

[4]There may be a concern that I am simply double counting events by combining Haaretz and Al Jazeera measures. However, the correlation between the two sources for Hamas (≈ 0.21) and Israel (≈ 0.063) conflict intensity scores is very small—suggesting that Haaretz and Al Jazeera are picking up different aspects of the conflict

[5]While other countries such as Turkey, and regional organizations such as the European Union and Arab League did make statements, they were not directly involved in the mediation process

every instance in which a given actor was mentioned, one of their leaders or representatives made a statement, or there was a reference to their involvement in the mediation efforts. Counts of mentions were then aggregated to the hourly-level to create a measure of attention. This count measure is broad, and intentionally agnostic to the actual content of statements made by the Egypt, the US, or the UN. Furthermore, I did not want to categorize individual statements as pro-Hamas or pro-Israel, given that it can be difficult to extract such intentions from statements, and many of the statements simply contained factual information about the mediation efforts.[6] The following (hypothetical) statements occurring in an hour:

- US Secretary State Hilary Clinton meets with Egyptian leaders to discuss ceasefire efforts.
- US President Barack Obama encourages a cease fire.
- UN Secretary General Ban ki-Moon expresses concern for civilians on both sides.
- Egyptian President Mohamed Morisi criticizes Israel's actions.

would yield a score of 2 for Egypt, 1 for the UN, and 2 for the US. As in the Hamas and Israel conflict intensity scores, I combined both Haaretz and Al Jazeera measures to create unified attention scores for Egypt, the US, and the UN.[7]

In order to code public communication issued by Hamas and Israel, I scraped data from the full 179 hours of the conflict from the *@IDFSpokesPerson* and *@AlQassamBrigade* Twitter feeds. I used the four-point scale in Table 2 to code each tweet and then aggregate them to the hourly-level.

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and there were not enough instances of them in either Haaretz's or Al Jazeera's live blogs (Haaretz 2012; Al Jazeera 2012) to construct a meaningful measure of attention, so I exclude them from the analysis.

[6]If the statements would have been coded as directed towards the individual actors, I would have needed to create 6 variables for international attention–US attention towards Israel, US attention towards Hamas etc. Given the limited $N = 179$, this would have decreased the degrees of freedom while increasing the number of assumptions in coding the data. Schrodt, Yonamine and Bagozzi (2013) have shown that other event studies that have used using counts largely come to similar conclusions, as those using a more ordinal scale

[7]There was also a low correlation between how the two sources covered Egypt (≈ 0.24), the US (≈ 0.095), and UN (≈ 0.024) actions.

The scale measured how threatening and aggressive the IDF and Hamas Twitter feeds were. The bulk of all tweets could be categorized as offensive actions (actions or threats against the other side) or victimization (actions that the other side carried out). Threats or reports of offensive actions were scored higher than reports of offensive actions taken by the other side (4 versus 3, and 2 versus 1). Tweets making emotional, or propagandistic appeals were coded as being more aggressive (4 and 2 versus 3 and 1). For instance the following *@AlQassamBrigade* tweet:

> "Oh, Zionists You have to drag yourselves out of hell, go back home now, go back to Garmany (sic), Poland, Russia, America and anywhere else #Gaza *-11:51 November 21, 2012.*"

would be coded as Offensive Propaganda (4). Whereas this *@AlQassamBrigade* tweet:

> "Al Qassam Brigades shelling Israeli targets with 224 projectiles for today, 1426 since Israel's aggression on #Gaza #GazaUnderAttack #Israel *-22:56 November 20, 2012.*"

would be coded as Neutral Offensive (3).

Score	**Description**	**Example**
4	Offensive Propaganda	Bragging about military strikes or capabilities; threats; justifying actions against other side, including the use of offensive photos.
3	Neutral Offensive	Neutral reports of own military action.
2	Victim Propaganda	Use of emotional appeals with respect to victimization by other side, including picture or videos of victims.
1	Neutral Victim	Neutral report on offensive action taken by other side.

Table 2: **Twitter Aggressiveness Scores**

Finally, perhaps the most unique aspect of the 2012 Gaza Conflict was the use of competing hashtags by Hamas (#GazaUnderAttack) and Israel (#IsraelUnderFire) to let supporters signal their support for one of the sides (Borger 2012). Previous research has used hashtag data to uncover clusters in Canadian politics (Small 2011) and polarization during the 2010 U.S. congressional midterm elections (Conover, Ratkiewicz, Francisco, Gonçalves, Menczer and Flammini 2011). The hashtag data were collected by searching the full Twitter firehose for mentions of #GazaUnderAttack and #IsraelUnderFire during the conflict. Individual tweet identification numbers[8] were recorded, and then the Twitter API was queried to put together a frequency count of mentions for each hashtag. The hashtag data contains 710,279 tweets, from 180,669 unique users, where the median and modal number of tweets per user was 1, mean number of Tweets per user was 3.9, and the most active user tweeted 2,020 times. Only 16.3% of tweets were retweets (99,779 tweets), less than 2% of tweets directly mentioned *@AlQassamBrigade* (10,996 tweets), and less than 2% of tweets also mentioned *@IDFSpokesperson* (13,994 tweets). The distribution of tweets and retweets per user containing the different hashtag highlights the fact that (1) the tweet volume was not simply driven by a handful of users tweeting hundreds times (or the *@AlQassamBrigade* or *@IDFSpokesperson*), but rather a majority of tweets were from a large number of unique users, (2) with a smaller subset showing a more active engagement. Frequencies counts for each hashtag mention were aggregated at the hourly level to create the hashtag counts time series.[9]

A possible alternative strategy would be to use sentiment analysis, i.e., automated text analysis to classify the opinions of the actual text of the tweets, instead of hashtags to measure public opinion on Twitter. Below I delineate, three arguments that make using the hashtags (#GazaUnderAttack and #IsraelUnderFire) preferable to sentiment analysis:

1. Twitter's limited number of characters (140), informal style, use of irony, and lack of grammar make machine learning-based sentiment analysis very difficult, and dictionary, or classification scheme-dependent (Kontopoulos, Berberidis, Dergiades and Bassiliades 2013; Martínez-Cámara, Martín-Valdivia, Urena-López and Montejo-Ráez 2014).

2. Many papers have used hashtags as means of classifying tweets (Kouloumpis, Wilson and Moore 2011; Romero, Meeder and Kleinberg 2011; Barberá et al. 2015), since hashtags serve "as topical markers, an indication to the context of the tweet or as the core idea expressed"

[8] A unique identification number for each tweet sent. See `https://dev.twitter.com/` for more information on the Twitter Application Programming Interface (API).

[9] I am indebted to XXXXX for providing the the tweet identification numbers and for helping me collect the individuals tweet data via the API.

(Tsur and Rappoport 2012, p. 643). Thus, instead of the analyst imposing a classification scheme, using hashtags allows users to signal their support or opposition themselves.

3. Most importantly, the two hashtags were widely circulated on Twitter, with users actively aware of the competing hashtags.[10] In the follow-up conflict in 2014, these hashtags were once again used to show support for either side.[11]

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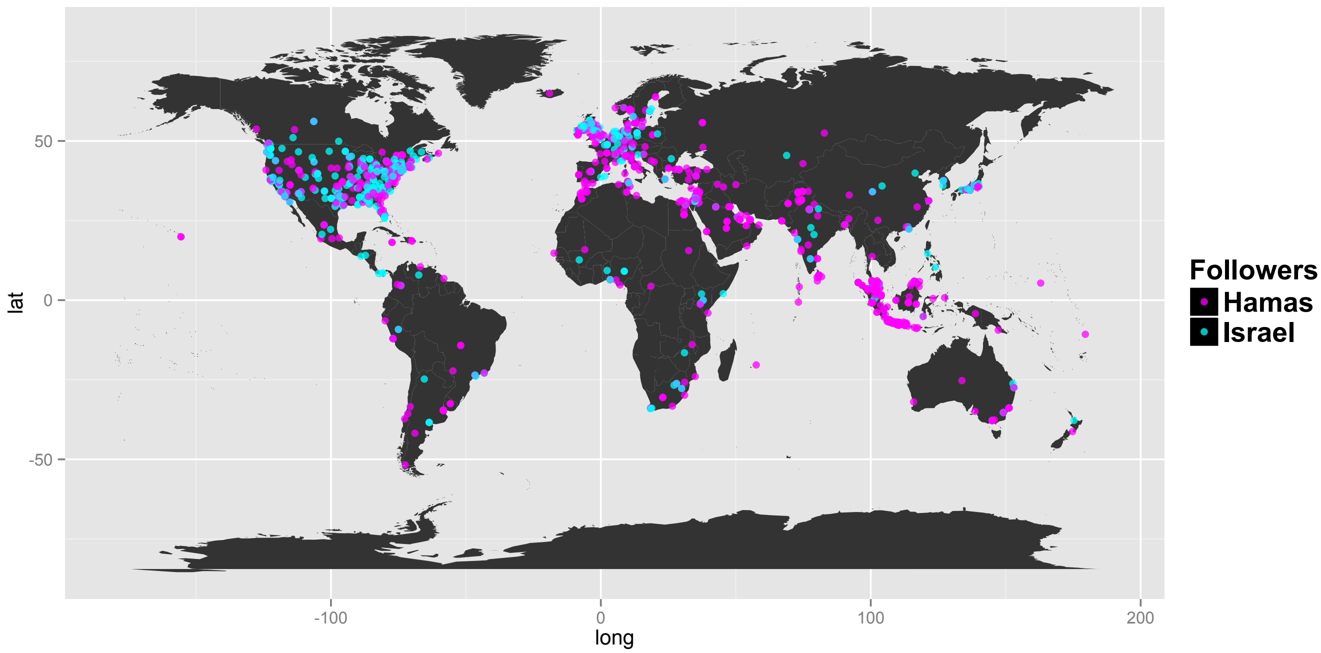
[10]See "Is Hamas Winning the Twitter War" in *The Washington Post* November 11, 2012; "Israel vs. Hamas: The first social-media war" in *The Philadelphia Inquirer* on November 17, 2012; and "The first social media war between Israel and Gaza" in *The Guardian* on December 6, 2012.

[11]See "Young Israelis Fight Hashtag Battle to Defend #IsraelUnderFire" in *The New York Times* on July 16, 2014; and "Israel and Hamas clash on social media" in *The Guardian* on July 16, 2014.

A.2 Geographic Distribution of Followers

Figure 1: **Twitter Followers Map**



Each dot represents a follower of *@AlQassamBrigade* (magenta) or *@IDFSpokesperson* (cyan). I randomly sampled the location data of 1,000 followers of each of the two Twitter feeds using the `twitteR` package in `R`. I then used Google's Location API to extract a latitude and longitude for each location that was able to be matched ($\approx 25\%$). The resulting map shows the distribution of followers.

A.3 In-Depth Structural Identification Discussion

Previous research in international relations suggests that conflict and diplomatic behavior in the presence of different audiences is dynamic and complex (Putnam 1988; Guisenger and Smith 2002; Brandt, Colaresi and Freeman 2008). Particularly in the 2012 Gaza Conflict, understanding the strategic calculus of Hamas and Israel–as they respond to each other on the battlefield, the international mediators, the other side's communication from their Twitter feeds, and public support via Twitter–requires a model complex enough to match the data generating process. Within a conflict system, certain variables are likely to respond contemporaneously to each other. For instance, previous research has shown that Israel's conflict intensity responds contemporaneously (within the hour) to Hamas's conflict intensity (Zeitzoff 2011), as it (Israel) has a sophisticated military predicated on quickly responding to Hamas. Conversely Hamas, as a the weaker opponent may be less willing to directly confront Israel (Arreguín-Toft 2006; Zeitzoff 2011). Thus a model that allows Israel's conflict intensity to respond within the hour to Hamas, directly influences Israel's subsequent conflict intensity, and also the subsequent values of the other variables as they react to Israel's conflict intensity. Comparing different models of contemporaneous relationships within a conflict system is important for testing hypotheses, because not only do the contemporaneous relationships influence the immediate response dynamics of the conflict, but they change the long-run trajectory of the conflict as they filter through the system.

In Tables 3-5, I explore different potential models of contemporaneous relationships through various configurations of the A_0 matrix. Given the complexity of delineating the structural relationships in a 9-variable BSVAR model (9 equations made up of 9 variables each), I break apart the models, into three separate tables, each exploring a key, strategic aspect of the conflict. In Table 3, I explore internal conflict variables and specifically whether the conflict variables (*I2H* and *H2I*) respond contemporaneously to the other side's communication (*IDF* and *AQB*). Table 4 explores how sensitive each side's strategic communication (via their Twitter feeds *IDF* and *AQB*) is to changes in the mediators' attention (*UN, Egypt*, and *US*). Table 5 looks as how public support (*#Gaza* and *#Israel*) influences strategic communication (*IDF* and *AQB*).

Tables 3-5 present a series of potential models (A_0 matrices). Each model is composed of 9 rows and 9 columns. The columns are equations and the rows are variables designated (or not designated) to have a contemporaneous relationship with the row variable. In each model, an X represents a "free" parameter to be estimated. The estimated free parameters correspond to the the row variable having a contemporaneous relationship with the column equation. Empty cells are assumed that row variables have no contemporaneous relationships.

As Brandt, Colaresi and Freeman (2008) and Brandt and Freeman (2009) argue, it is important when determining different potential A_0 models that theory guide their plausibility. Following Zeitzoff (2011), for all models I restrict *H2I* from responding contemporaneously to *I2H*. I assume that Israel, with its superior military technology (Gross 2010), would be able to respond contemporaneously to Hamas, but not vice versa.[12] I also allow both both Hamas's and Israel's public communication (*AQB* and *IDF*) to respond to both each other, and also the conflict (*H2I* and *I2H*) contemporaneously. The role of each side's Twitter feeds, to report on the conflict, and cast their side's role in the conflict in a positive light (Rothman 2012), makes this a fairly benign assumption. Finally, I restrict mediators (*US, Egypt* and *UN*) such that they do not respond contemporaneously (within the hour) to the conflict (*H2I* and *I2H*), or to the communication of Hamas and Israel (*AQB* and *IDF*). Given the speed of diplomacy,[13] and time differences between the various mediators, this restriction is fairly reasonable.[14]

Table 3 presents the *Baseline* model and then explores the different model specifications for allowing *I2H* and *H2I* to respond to the other side's communication (*AQB* or *IDF*). It explores whether shifts in the other side's Twitter feed led to immediate responses in Israel and Hamas's conflict intensity. For instance the *IDF Conflict* model allows *I2H* to respond contemporaneously to *AQB*. Conversely the *AQB Conflict*, allows *H2I* to respond contemporaneously to *IDF*, and the *Conflict Both*, allows both *I2H* and *H2I* to respond immediately shocks in the other side's communication.

In Table 4, I build upon Table 3, and explore different configurations of how Hamas and Israel respond to international attention from the mediators (*UN, Egypt,* and *US*) via their Twitter feeds (*AQB* and *IDF*). For instance, previous research finds that democratic states are more responsive to international pressures via mediation Dixon (1994). This is captured in Table 3 with the *Mediator IDF* model, which allows *IDF* to respond contemporaneously to shocks in the other international mediators, while *AQB* does not. Other theories, suggest that belligerents may be more likely to respond to allied/biased mediators (Calvert 1985; Kydd 2003), which the *Mediator Biased* model

[12]Additionally, when I allow *H2I* to respond contemporaneously to I2H in the best fitting model (*Hashtag Model* from Table 5), the log marginal data density and resulting Bayes Factor is significantly worse (-3852.90) than the *Hashtag Biased* (-3843.72).

[13]See Nickles (2009) for a discussion on diplomatic speed with reference to the advent of the telegraph.

[14]All models in Tables 3-5 (and all VAR models) implicitly assume that variables respond contemporaneously to their own innovations. This is captured by the X's on the main diagonal.

captures by allowing *IDF* to respond contemporaneously to *US*, and AQB to *Egypt*.

Table 5 builds upon Table 4, and explores the contemporaneous relationship between communication (the Twitter feeds AQB and *IDF*), and changes in public support via changes in the frequency of *#Gaza* and *#Israel*. Baseline specification assume that *#Gaza* (*#Israel*) responds to contemporaneous changes in *I2H* (*H2I*), AQB (*IDF*) and the other hashtag *#Israel* (*#Gaza*). These models stem from the explicit role of the Hamas and Israeli Twitter feeds— to advance their own hashtag, denigrate the other side's actions, and react to the opposing Twitter feeds.[15] The key question is whether AQB or *IDF* both react to shifts in public support to both sides (*Hashtag Both*), only the *IDF* responds to contemporaneous changes in public support (*Hashtag IDF*), only AQB responds to contemporaneous changes in public support (*Hashtag* AQB), or whether each side responds contemporaneously to their own constituencies (*IDF* to *#Israel*, and AQB to *#Gaza*) in the *Hashtag Biased* model.

To test which model best explains the data I fit a 5-lag BSVAR for each of the 13 models proposed in Tables 3-5. Given the large number of parameters to be estimated and complex dynamics, I use a relatively informed prior. This prior shrinks the higher order lags towards zero by putting inexact restrictions on lagged values. The prior is then correlated across equations via the contemporaneous relationships, allowing beliefs about the structure of contemporaneous relationship to be included in the prior (Brandt, Colaresi and Freeman 2008, p. 357-358).[16]

The BSVAR framework also provides a useful way of testing the in-sample fits of the competing contemporaneous models in Tables 3-5 via the log marginal data density ($log(MDD)$) (Brandt, Colaresi and Freeman 2008; Brandt and Freeman 2009). Comparing the log marginal data densities from two models (i and j) $log(MDD_i)$-$log(MDD_i)$ yields a log Bayes Factor. The Bayes Factor provides a relative odds ratio between two models, with larger values indicating a significantly

[15]Furthermore, alternative specifications that allow *#Gaza* and *#Israel* to react to both conflict actors (*I2H* and *H2I*) and Twitter feeds (*IDF* and AQB) contemporaneously fit significantly worse log marginal data density (-3860.19) than the *Hashtag Biased* model in Table 7 (-3843.72). Not having either *#Gaza* and *#Israel* react contemporaneously to either Twitter feeds or conflict feeds also results in a significantly poorer fit (-3859.51).

[16]IRF results from a looser prior are presented in the IRF Results Robustness section in the Supplementary Information. The results largely match those from the informed model.

better model fit in favor of $Model_i$ (Geweke 2005).

Several interesting observations can be gleaned from Table 6. (1) The $log(MDD)$ in the top third of Table 6 compares models which allow *I2H* to react contemporaneously to AQB (*Conflict IDF*), or *H2I* to *IDF* (*Conflict* AQB), or both (*Conflict Both*) to the *Baseline* model, which does not allow either to react contemporaneous to the other's communication on Twitter. The differences in the $log(MDD)$ densities between the three models (excluding the *Baseline*) are small, and compared to the *Baseline* model they are also fairly negligible.[17] However, given the technical superiority of the Israeli military compared to Hamas's, theoretically it makes more sense to allow Israel's conflict intensity to respond contemporaneously to Hamas's communication rather than vice versa (i.e. *Conflict IDF* makes more sense relative to the *Conflict* AQB).[18] Moreover, including the other contemporaneous relationships from the *Hashtag Biased* model and allowing *H2I* to respond contemporaneously to *IDF* leads to a significantly worse (smaller) $log(MDD)$ (-3858.001) than the *Hashtag Biased* model (-3843.72). The same is true when allowing both *H2I* and *I2H* to react contemporaneously to the *IDF* and AQB in the *Hashtag Biased* model (-3857.52).[19] This suggests, that Israel's conflict intensity was much quicker to react to what Hamas was saying on Twitter than vice versa. 2) The middle third of Table 6 uses the *Conflict IDF* specification, and then tests whether the *IDF* and AQB respond to attention from the three international mediators. A comparison of the different $log(MDD)$ and Bayes factors strongly suggest that they do not. The Bayes factor for the *Conflict IDF* model, where neither *IDF* or AQB respond contemporaneously, is much larger compared to any of the *Mediator* models which allow the *IDF* and or AQB to react to international mediators ($\approx e^{10}$). It is not surprising that the influence of international mediators takes a longer time to influence the strategic communication of conflict participants. This is not to say that international mediators do not have an effect on Hamas's or Israel's actions

[17] $3.67 \approx e^{1.3}$ for the difference between *Conflict IDF* and the *Baseline* model.

[18] IRF results presented in the Supplementary allow Hamas's conflict (H2I) to respond to Israel's conflict (I2H) and communication (IDF) contemporaneously with both its conflict and communication. The main finding that Israel's conflict intensity is more constrained by an increase in public support for Hamas on social media are confirmed.

[19] Both of these models yield very large ($\approx e^{14}$) Bayes factors when compared to the *Hashtag Biased* model, further showing the latter is a better fit.

or communications, but rather that their effect may take longer to materialize. 3) Finally the bottom third of Table 6 examines whether *IDF* and AQB respond contemporaneously to changes in *#Gaza* and *#Israel*. The *Hashtag Biased* model—where AQB responds contemporaneously to *#Gaza*, and *IDF* to *#Israel*, presents overall the best fit of all 13 models, with the largest $log(MDD)$. The *Hashtag Biased* has a Bayes Factor of $\approx e^{4.3}$ compared to the closest competing model *Hashtag Both*—a significant improvement.

The *Hashtag Biased* provides the best fit of the data,[20] and also interesting insights on the strategies of Hamas and Israel. Israel's conflict intensity reacts contemporaneously to changes in Hamas's conflict intensity and to its communication on Twitter, echoing previous findings that the stronger actor (Israel) would be more reactive to the weaker actor (Hamas) than vice versa (Zeitzoff 2011). Another more innovative finding, is the fact that both Israel and Hamas contemporaneously respond to shifts in international public support, via changes in their respected hashtags. This provides a unique insight into how Twitter and other social media allows states to influence international audiences and vice versa. In turn, public support from diaspora communities then influences state behavior.

A.4 Threat to Inference of Results

Perhaps social media sympathy for Hamas simply spikes following heavy Israeli action? Thus the finding that social media support for Hamas decreases Israels conflict intensity may simply be picking up spikes in support for Hamas just as Israels strategic goals have been met (i.e., a

[20]There may be a concern that the models from Tables 3-5 build upon each other. For instance, Table 4 takes the best fit from Table 3 and tests different permutations of relationship with the mediators. And, Table 5, takes the best fit from Table 4 and then tests different effects of the hashtag frequency. However, it may be that including the insights and structural relationship from the *Hashtag* model in Table 5, and then retesting the relationship in Tables 3 or 4 leads to a different results. I reexamine the $log(MDD)$ from the A_0 models in Tables 3 and 4 and find no difference in the substantive interpretations. The best fit models allow Israel's conflict intensity *I2H* to respond contemporaneously to Hamas's communication (AQB), and Hamas's conflict intensity (*H2I*) to not respond contemporaneously to Israel's communication (*IDF*). Also, the best fit restricts Hamas's and Israel's communication (AQB and *IDF*) from responding contemporaneously to the international mediators. This confirms that far and away the best fit of any (theoretically sound) permutation is the *Hashtag Biased* model.

spurious relationship). In addition to the qualitative evidence presented in the main text in favor of the importance of social media in influencing Israel's conflict decisions, four statistical arguments minimize this concern.

1. Both of the hashtag time series (*#Gaza* and *#Israel*) are seasonally adjusted–removing any kind of regularized pattern due to the time of day.

2. The correlation between the regularized seasonal component for support for Hamas *(#Gaza)* and Israels conflict intensity (*I2H*) is fairly weak (0.21). Thus the support for Hamas does not appear to be peaking at the same time of day as Israels conflict intensity.

3. Table 9 shows that seasonally adjusting all variables including Israels conflict intensity (*I2H*) does not influence the fundamental findings.

4. If Israels actions were leading to spikes in support for Hamas on social media, then Israels conflict intensity (*I2H*) should strongly predict (Granger cause) support for Hamas on social media (*#Gaza*). As Figure 4 in the Appendix in the main text shows, *I2H* weakly Granger causes (lag=5) *#Gaza* (F=1.66, and *p-valu*e=0.15). Thus, support for Hamas is not simply reacting to Israel actions.

A.5 IRF Results Robustness

Tables 7-12 present robustness checks on the IRF results from the main text (Figure 2). Each table presents the results from 10,000 burn-in draws, 50,000 MCMC draws with the exception of Table 12. Table 7 uses a comparatively looser prior to estimate the IRF. Table 8 increases the lag length from 5 hours, to 9 hours. Table 9 seasonally adjusts all variables, not just for #Gaza or #Israel. Table 10 uses a different coding scheme for the *AQB* and *IDF* Twitter variables. Instead of coding each tweet along the 4-point scale from Table 2, I simply use the raw tweet counts for *AQB* and *IDF*. Table 12 looks at what happens when Hamas's conflict intensity (*H2I*) is allowed to react contemporaneously to Israel's strategic communication (*IDF* and *I2H*). And, Table 12 tests the results of the MCMC procedure have converged, by doubling the number of burn-ins and draws (20,000 burn-in draws, 100,000 MCMC draws).

The main findings from the text are confirmed. 1) Increases in public support on social media for Hamas (*#Gaza*) decrease Israel's conflict intensity more than the international mediators, and much more than shocks in public support for Israel (*#Israel*) affect Hamas's conflict intensity. 2) Israel's communication on Twitter (*IDF*) increases in its aggressiveness and activity following increases in public support for Hamas, while the mediators have little effect on either actor's communication. 3) Finally, public support on social media for Israel increases shocks in public support on social media for Hamas, but not vice versa.

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Model	**Variable**	**H2I**	**I2H**	**IDF**	**AQB**	**UN**	**Egypt**	**US**	**#Gaza**	**#Israel**
Baseline	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF		X	X	X					
	AQB	X		X	X					
	UN					X				
	Egypt						X			
	US							X		
	#Gaza								X	
	#Israel									X
IDF Conflict	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF		X	X	X					
	AQB	X	X	X	X					
	UN					X				
	Egypt						X			
	US							X		
	#Gaza								X	
	#Israel									X
AQB Conflict	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF	X	X	X	X					
	AQB	X		X	X					
	UN					X				
	Egypt						X			
	US							X		
	#Gaza								X	
	#Israel									X
Both Conflict	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF	X	X	X	X					
	AQB	X	X	X	X					
	UN					X				
	Egypt						X			
	US							X		
	#Gaza								X	
	#Israel									X

Table 3: **Contemporaneous Relationship (Conflict)** Each block specifies the contemporaneous relationships and restrictions in the A_0 matrix. Columns correspond to contemporaneous equations and rows to the variables that do (or do not) have contemporaneous relationships with the column variables. The Xs in each cell represent free parameters, or those estimated to have a contemporaneous impact on a given column variable, while the empty cells are zero restrictions. A zero restriction indicates that the given row variable has no contemporaneous relationship to the row variable (in the column equation).

Model	**Variable**	**H2I**	**I2H**	**IDF**	**AQB**	**UN**	**Egypt**	**US**	**#Gaza**	**#Israel**
Mediator Both	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF		X	X	X					
	AQB	X	X	X	X					
	UN			X	X	X				
	Egypt			X	X		X			
	US			X	X			X		
	#Gaza								X	
	#Israel									X
Mediator IDF	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF		X	X	X					
	AQB	X	X	X	X					
	UN			X		X				
	Egypt			X			X			
	US			X				X		
	#Gaza								X	
	#Israel									X
Mediator AQB	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF		X	X	X					
	AQB	X	X	X	X					
	UN				X	X				
	Egypt				X		X			
	US				X			X		
	#Gaza								X	
	#Israel									X
Mediator Biased	*H2I*	X	X	X	X					
	I2H		X	X	X					
	IDF		X	X	X					
	AQB	X	X	X	X					
	UN					X				
	Egypt				X		X			
	US			X				X		
	#Gaza								X	
	#Israel									X

Table 4: **Contemporaneous Relationship (Mediator)**

Model	**Variable**	**H2I**	**I2H**	**IDF**	**AQB**	**UN**	**Egypt**	**US**	**#Gaza**	**#Israel**
Hashtag Baseline	*H2I*	X	X	X	X					X
	I2H		X	X	X				X	
	IDF		X	X	X					X
	AQB	X	X	X	X				X	
	UN					X				
	Egypt						X			
	US							X		
	#Gaza								X	X
	#Israel								X	X
Hashtag Both	*H2I*	X	X	X	X					X
	I2H		X	X	X				X	
	IDF		X	X	X					X
	AQB	X	X	X	X				X	
	UN					X				
	Egypt						X			
	US							X		
	#Gaza			X	X				X	X
	#Israel			X	X				X	X
Hashtag IDF	*H2I*	X	X	X	X					X
	I2H		X	X	X				X	
	IDF		X	X	X					X
	AQB	X	X	X	X				X	
	UN					X				
	Egypt						X			
	US							X		
	#Gaza			X					X	X
	#Israel			X					X	X
Hashtag AQB	*H2I*	X	X	X	X					X
	I2H		X	X	X				X	
	IDF		X	X	X					X
	AQB	X	X	X	X				X	
	UN					X				
	Egypt						X			
	US							X		
	#Gaza				X				X	X
	#Israel				X				X	X
Hashtag Biased	*H2I*	X	X	X	X					X
	I2H		X	X	X				X	
	IDF		X	X	X					X
	AQB	X	X	X	X				X	
	UN					X				
	Egypt						X			
	US							X		
	#Gaza				X				X	X
	#Israel			X					X	X

Table 5: **Contemporaneous Relationship (Hashtag)**

Model	Log Marginal Data Density $log(MDD)$
Baseline	-3860.33
Conflict IDF	-3858.99
Conflict AQB	-3858.97
Conflict Both	-3857.78
Mediator Both	-3876.09
Mediator IDF	-3868.74
Mediator AQB	-3868.07
Mediator Biased	-3867.75
Hashtag Baseline	-3860.30
Hashtag Both	-3848.01
Hashtag IDF	-3855.90
Hashtag AQB	-3859.00
Hashtag Biased	-3843.72

Table 6: **Posterior Model Summaries** Posterior statistics are based on 5-lag model. Estimates are calculated via the `MSBVAR` package in `R` (Brandt and Appleby 2012) using 10,000 burn-in draws, and 20,000 Markov chain Monte Carlo (MCMC) draws.

Shock In	*Response By*	*Cumulative Median Response After 12 hrs.*	*68% Regions*	*90% Regions*
H2I	I2H	0.18	(0.05,0.38)	(-1.53, 2.23)
I2H	H2I	-0.07	(-0.19, 0.07)	(-0.90, 0.78)
IDF	H2I	-0.08	(-0.12, -0.05)	(-0.40, 0.21)
IDF	AQB	0.11	(0.07, 0.15)	(-0.40, 0.74)
AQB	I2H	0.85	(0.46, 1.43)	(-2.34, 4.68)
AQB	IDF	0.16	(-0.25, 0.62)	(-1.87, 2.31)
#Gaza	H2I	-0.61	(-0.68, -0.51)	(-1.21, -0.08)
#Gaza	I2H	-2.46	(-2.80, -2.13)	(-4.70, -0.41)
#Israel	H2I	-0.32	(-0.47, -0.24)	(-0.96, 0.10)
#Israel	I2H	-1.22	(-1.39,-1.06)	(-2.58, -0.27)
#Gaza	IDF	0.63	(0.48, 0.73)	(-0.19, 1.48)
#Gaza	AQB	-0.89	(-1.07, -0.72)	(-1.93, 0.17)
#Israel	IDF	0.36	(0.09, 0.61)	(-0.82, 1.47)
#Israel	AQB	-0.05	(-0.17, 0.10)	(-0.82, 0.81)
#Gaza	#Israel	1.24	(0.57, 2.03)	(-0.79, 3.49)
#Israel	#Gaza	0.26	(0.11, 0.44)	(-0.20, 0.91)
UN	H2I	0.53	(0.53, 0.53)	(0.53, 0.85)
UN	I2H	0.41	(0.41, 0.41)	(0.41, 0.42)
UN	IDF	0.04	(0.04, 0.04)	(0.04, 0.04)
UN	AQB	-0.02	(-0.02, -0.02)	(-0.02, -0.02)
Egypt	H2I	0.53	(0.53, 0.53)	(0.53, 0.83)
Egypt	I2H	0.25	(0.25, 0.25)	(0.25, 0.26)
Egypt	IDF	-0.002	(-0.002,-0.002)	(-0.002 -0.002)
Egypt	AQB	-0.19	(-0.19, -0.19)	(-0.19, -0.19)
US	H2I	0.54	(0.54, 0.54)	(0.54, 0.81)
US	I2H	0.50	(0.50, 0.50)	(0.50, 0.53)
US	IDF	0.14	(0.14, 0.14)	(0.14, 0.21)
US	AQB	-0.05	(-0.05, -0.05)	(-0.05, -0.05)

Table 7: **Cumulative Impulse Response Functions from BSVAR Hashtag Biased (5-lag model with Looser Prior)**
$\lambda_0 = 0.8$, λ_1=0.3, $\lambda_3 = 1.8$, $\lambda_4 = 0.5$, $\lambda_5 = .25$, $\mu_5 = 0$, $\mu_6 = 0$

Shock In	*Response By*	*Cumulative Median Response After 18 hrs.*	*68% Regions*	*90% Regions*
H2I	I2H	0.99	(0.94, 1.05)	(-0.78, 2.96)
I2H	H2I	-0.08	(-0.11, -0.03)	(-0.99, 0.85)
IDF	H2I	-0.17	(-0.18, -0.16)	(-0.48, 0.11)
IDF	AQB	0.30	(0.28, 0.32)	(-0.27, 0.94)
AQB	I2H	-0.25	(-0.45, -0.06)	(-4.93, 4.43)
AQB	IDF	-0.85	(-1.07, -0.65)	(-3.63, 1.76)
#Gaza	H2I	-0.84	(-0.88, -0.77)	(-1.50, -0.17)
#Gaza	I2H	-1.08	(-1.26, -0.88)	(-3.29, 1.18)
#Israel	H2I	-0.66	(-0.73, -0.58)	(-1.35, 0.08)
#Israel	I2H	-0.52	(-0.61, -0.44)	(-1.99, 1.00)
#Gaza	IDF	1.39	(1.30, 1.45)	(0.41, 2.37)
#Gaza	AQB	0.73	(0.62, 0.84)	(-0.46, 1.88)
#Israel	IDF	1.72	(1.59, 1.88)	(0.62, 3.09)
#Israel	AQB	0.95	(0.88, 1.02)	(-0.05, 2.01)
#Gaza	#Israel	2.56	(2.25, 3.25)	(0.16, 6.46)
#Israel	#Gaza	0.81	(0.67, 0.91)	(0.06, 1.69)
UN	H2I	0.61	(0.61, 0.61)	(0.61, 0.61)
UN	I2H	0.24	(0.24, 0.24)	(0.24, 0.24)
UN	IDF	-0.03	(-0.03, -0.03)	(-0.03, -0.03)
UN	AQB	0.20	(0.20, 0.20)	(0.20, 0.20)
Egypt	H2I	0.65	(0.65, 0.65)	(0.65, 0.65)
Egypt	I2H	0.56	(0.56, 0.56)	(0.56, 0.56)
Egypt	IDF	0.02	(0.02, 0.02)	(0.02, 0.02)
Egypt	AQB	0.07	(0.07, 0.07)	(0.07, 0.07)
US	H2I	0.67	(0.67, 0.67)	(0.67,0.67)
US	I2H	0.44	(0.44, 0.44)	(0.44, 0.44)
US	IDF	-0.25	(-0.25, -0.25)	(-0.25, -0.25)
US	AQB	0.09	(0.09, 0.09)	(0.09, 0.09)

Table 8: **Cumulative Impulse Response Functions from BSVAR Hashtag Biased (9-lag model)**

Shock In	*Response By*	*Cumulative Median Response After 12 hrs.*	*68% Regions*	*90% Regions*
H2I	I2H	-0.19	(-0.24, -0.15)	(-1.22, 0.73)
I2H	H2I	-0.48	(-0.55, -0.44)	(-0.99, -0.14)
IDF	H2I	-0.13	(-0.17, -0.10)	(-0.51, 0.18)
IDF	AQB	-0.08	(-0.18, -0.01)	(-0.90, 0.68)
AQB	I2H	0.83	(0.54, 1.22)	(-1.81, 3.90)
AQB	IDF	0.71	(0.44, 1.05)	(-0.85, 2.39)
#Gaza	H2I	-0.37	(-0.45, -0.28)	(-0.84, 0.04)
#Gaza	I2H	-2.06	(-2.41, -1.71)	(-4.33, 0.05)
#Israel	H2I	-0.31	(-0.41, -0.20)	(-0.79, 0.20)
#Israel	I2H	-0.89	(-1.05, -0.71)	(-2.26, 0.24)
#Gaza	IDF	0.63	(0.47, 0.77)	(-0.11, 1.42)
#Gaza	AQB	0.01	(-0.18, 0.19)	(-1.05, 1.00)
#Israel	IDF	0.53	(0.27, 0.77)	(-0.61, 1.60)
#Israel	AQB	0.24	(0.11, 0.37)	(-0.60, 1.09)
#Gaza	#Israel	2.55	(2.18, 3.77)	(1.06, 5.24)
#Israel	#Gaza	-0.16	(-0.37, -0.03)	(-0.73, 0.43)
UN	H2I	0.14	(0.14, 0.14)	(0.14, 0.16)
UN	I2H	0.38	(0.38, 0.38)	(0.38, 0.38)
UN	IDF	-0.03	(-0.03, -0.03)	(-0.03, -0.03)
UN	AQB	0.29	(0.29, 0.29)	(0.29, 0.43)
Egypt	H2I	0.08	(0.08, 0.08)	(0.08, 0.09)
Egypt	I2H	0.14	(0.14, 0.14)	(0.13, 0.14)
Egypt	IDF	-0.03	(-0.03, -0.03)	(-0.03, -0.02)
Egypt	AQB	0.003	(0.003, 0.003)	(0.003, 0.01)
US	H2I	0.14	(0.14, 0.14)	(0.14, 0.14)
US	I2H	0.30	(0.30, 0.30)	(0.29, 0.30)
US	IDF	-0.07	(-0.07, -0.07)	(-0.07, -0.06)
US	AQB	0.29	(0.29, 0.29)	(0.29, 0.46)

Table 9: **Cumulative Impulse Response Functions from BSVAR Hashtag Biased (5-lag model with ALL variables seasonally adjusted)**

Shock In	*Response By*	*Cumulative Median Response After 12 hrs.*	*68% Regions*	*90% Regions*
H2I	I2H	0.23	(0.14, 0.31)	(-1.32, 1.76)
I2H	H2I	0.35	(0.24, 0.50)	(-0.36, 1.20)
IDF	H2I	-0.22	(-0.25, -0.19)	(-0.48, -0.02)
IDF	AQB	0.28	(0.25, 0.33)	(-0.02, 0.71)
AQB	I2H	1.51	(1.19, 2.08)	(-1.04, 4.72)
AQB	IDF	0.38	(0.12, 0.65)	(-0.88, 1.66)
#Gaza	H2I	-0.25	(-0.34, -0.15)	(-0.75, 0.21)
#Gaza	I2H	-0.38	(-0.63, -0.12)	(-1.97, 1.20)
#Israel	H2I	-0.21	(-0.32, -0.13)	(-0.75, 0.22)
#Israel	I2H	-0.33	(-0.46, -0.20)	(-1.31, 0.58)
#Gaza	IDF	0.38	(0.28, 0.48)	(-0.10, 0.90)
#Gaza	AQB	-0.21	(-0.34, -0.07)	(-0.97, 0.51)
#Israel	IDF	0.25	(0.10, 0.39)	(-0.45, 0.93)
#Israel	AQB	0.05	(-0.04, 0.14)	(-0.57, 0.67)
#Gaza	#Israel	3.30	(2.85, 4.28)	(1.31, 5.92)
#Israel	#Gaza	-0.22	(-0.44, -0.09)	(-0.83, 0.41)
UN	H2I	0.45	(0.45, 0.45)	(0.45, 0.71)
UN	I2H	0.14	(0.14, 0.14)	(0.14, 0.17)
UN	IDF	0.06	(0.06, 0.06)	(0.06, 0.06)
UN	AQB	0.34	(0.34, 0.34)	(0.34, 0.49)
Egypt	H2I	0.57	(0.57, 0.57)	(0.57 0.92)
Egypt	I2H	0.11	(0.11, 0.11)	(0.11, 0.12)
Egypt	IDF	0.01	(0.01, 0.01)	(0.01,0.01)
Egypt	AQB	0.33	(0.33, 0.33)	(0.33, 0.43)
US	H2I	0.46	(0.46, 0.46)	(0.46, 0.70)
US	I2H	0.15	(0.15, 0.15)	(0.15, 0.15)
US	IDF	0.16	(0.16,0.16)	(0.16,0.16)
US	AQB	0.33	(0.33, 0.33)	(0.33, 0.46)

Table 10: **Cumulative Impulse Response Functions from BSVAR Hashtag Biased (5-lag model with raw tweet counts.)** Instead of assigning each tweet from the *IDF* or *AQB* a 1 to 4, based on their content, this table shows the results using raw tweet counts using the same set-up as Table 5 in the main text.

Shock In	*Response By*	*Cumulative Median Response After 12 hrs.*	*68% Regions*	*90% Regions*
H2I	I2H	0.12	(-0.28, 0.54)	(-2.40, 2.62)
I2H	H2I	0.48	(0.34, 0.68)	(-0.33, 1.46)
IDF	H2I	-0.38	(-0.47, -0.35)	(-0.84, -0.06)
IDF	AQB	0.42	(0.32, 0.59)	(-0.55, 1.65)
AQB	I2H	0.99	(0.48, 1.39)	(-1.97, 3.94)
AQB	IDF	1.11	(0.85, 1.75)	(-0.88, 1.66)
#Gaza	H2I	-0.16	(-0.27, -0.05)	(-0.75, 0.41)
#Gaza	I2H	-0.53	(-0.78, -0.28)	(-1.94, 0.88)
#Israel	H2I	-0.081	(-0.24, -0.08)	(-0.78, 0.62)
#Israel	I2H	-0.23	(-0.36, -0.08)	(-1.16, -0.23)
#Gaza	IDF	0.78	(0.63, 0.91)	(0.10, 1.55)
#Gaza	AQB	0.68	(0.34, 1.02)	(-1.17, 2.58)
#Israel	IDF	0.35	(0.16, 0.53)	(-0.49, 1.16)
#Israel	AQB	0.68	(0.51, 0.89)	(-0.44, 2.04)
#Gaza	#Israel	3.07	(2.59, 4.00)	(1.08, 5.58)
#Israel	#Gaza	-0.20	(-0.42, -0.07)	(-0.83, 0.44)
UN	H2I	0.13	(0.13, 0.13)	(0.13, 0.13)
UN	I2H	0.11	(0.11, 0.11)	(0.11, 0.11)
UN	IDF	0.23	(0.23, 0.23)	(0.23, 0.31)
UN	AQB	-0.15	(-0.15, -0.15)	(-0.15, -0.15)
Egypt	H2I	0.23	(0.23, 0.23)	(0.23 0.26)
Egypt	I2H	0.09	(0.09, 0.09)	(0.09, 0.09)
Egypt	IDF	0.26	(0.26, 0.26)	(0.26,0.37)
Egypt	AQB	-0.31	(-0.31, -0.31)	(-0.34, -0.31)
US	H2I	0.12	(0.12, 0.12)	(0.12, 0.12)
US	I2H	0.10	(0.10, 0.10)	(0.10, 0.10)
US	IDF	0.28	(0.28, 0.28)	(0.28, 0.44)
US	AQB	-0.16	(-0.16, -0.16)	(-0.16, -0.16)

Table 11: **Cumulative Impulse Response Functions from BSVAR 5-lag model (allowing H2I to react contemporaneously to IDF and I2H)**

Shock In	*Response By*	*Cumulative Median Response After 12 hrs.*	*68% Regions*	*90% Regions*
H2I	I2H	0.19	(0.07, 0.31)	(-1.68, 2.13)
I2H	H2I	0.004	(-0.13, 0.15)	(-0.78, 0.84)
IDF	H2I	-0.14	(-0.19, -0.10)	(-0.52, 0.17)
IDF	AQB	0.22	(0.17, 0.29)	(-0.32, 0.92)
AQB	I2H	1.22	(0.88, 1.82)	(-1.95, 5.17)
AQB	IDF	-0.07	(-0.49, 0.36)	(-2.25, 2.11)
#Gaza	H2I	-0.59	(-0.69, -0.49)	(-1.16, -0.10)
#Gaza	I2H	-2.07	(-2.39, -1.75)	(-4.23, -0.11)
#Israel	H2I	-0.32	(-0.46, -0.25)	(-0.94, 0.09)
#Israel	I2H	-1.10	(-1.26, -0.96)	(-2.43, -0.10)
#Gaza	IDF	0.65	(0.48, 0.81)	(-0.14, 1.50)
#Gaza	AQB	-0.40	(-0.58, -0.21)	(-1.41, 0.62)
#Israel	IDF	0.72	(0.46, 0.95)	(-0.42, 1.79)
#Israel	AQB	0.12	(0.002, 0.27)	(-0.66, 0.99)
#Gaza	#Israel	1.28	(0.58, 2.10)	(-0.87, 3.62)
#Israel	#Gaza	0.24	(0.05, 0.40)	(-0.27, 0.92)
UN	H2I	0.55	(0.55, 0.55)	(0.55, 0.88)
UN	I2H	0.41	(0.41, 0.41)	(0.41, 0.44)
UN	IDF	0.04	(0.04, 0.04)	(0.04, 0.04)
UN	AQB	-0.13	(-0.13, -0.13)	(-0.13, -0.13)
Egypt	H2I	0.57	(0.57, 0.57)	(0.57 0.93)
Egypt	I2H	0.14	(0.14, 0.14)	(0.14, 0.14)
Egypt	IDF	-0.0002	(-0.0002 -0.0002)	(-0.0002,-0.0002)
Egypt	AQB	-0.24	(-0.24, -0.24)	(-0.24, -0.24)
US	H2I	0.55	(0.55, 0.55)	(0.55, 0.84)
US	I2H	0.54	(0.54, 0.54)	(0.54, 0.58)
US	IDF	0.04	(0.04, 0.04)	(0.04, 0.10)
US	AQB	-0.17	(-0.17, -0.17)	(-0.17, -0.17)

Table 12: **Cumulative Impulse Response Functions from BSVAR 5-lag model (20,000 burn-in draws, 100,000 MCMC draws)**