Supplementary Files
A Manifesto, in 140 Characters or Fewer: Social Media as a Tool of Rebel Diplomacy in the Libyan Civil War

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In this Appendix we present further data descriptions and plots. Data and replication materials will be released upon publication of this article.

1 Assessing Libya in 2010

As noted in the Research Design section of the main text, Libya, in many respects, appears to be a fairly typical state at risk of civil war onset in 2010, the year prior to the onset of its civil conflict. While the literature on civil war onset is vast, several core, robust results have emerged that allow us to evaluate the extent to which Libya is representative of states likely to experience civil conflict in a given year. Thus, to evaluate whether Libya seems to be a representative case of a civil war state or not, we compare Libya in 2010 to the universe of cases in 2010 in order

Collier and Hoeffler (2004); Hegre and Sambanis (2006), among others, note that states that produce significant quantities of primary commodities, such as oil, and states that export large quantities of primary commodities are at a much higher risk of civil war. Using data from Ross (2013), we compare Libya to all states in 2010, and find that Libya is in the 90th percentile for total oil production, and the 92nd percentile for oil exports. These data indicate that prior to the civil war, Libya was among the most prolific oil producers and exporters in the world, a fact that increases its risk of experiencing civil conflict.

Similarly, drawing on data and findings from Cederman, Wimmer and Min (2010), states with a large number of ethnic groups excluded from power are at a higher risk of civil conflict. In 2010, Libya excluded 3 groups from power, placing it in the 75th percentile of states in 2010, indicating that Libya excluded far more groups from power than most states, again increasing its risk of civil conflict.

Moreover, Sambanis (2001) and Hegre and Sambanis (2006) among many others have noted the importance of studying neighborhood effects as an important risk factor in generating a new civil conflict. States with neighbors experiencing civil conflict are themselves at a higher risk of experiencing civil conflict, as are states in relatively autocratic neighborhoods. In 2010, Libya had three contiguous neighbors experiencing a civil conflict: Chad, Algeria and Sudan (Gleditsch et al., 2002). Moreover, Libya's neighborhood, which we code as North Africa and the Middle East, is quite authoritarian, having an average regime type of -2.4 in 2010 (Marshall and Jaggers, 2002). Taken together, the fact that Libya was located in a relatively autocratic neighborhood with multiple ongoing civil wars likely increased its risk of civil conflict dramatically.

Other indicators of the risk of civil conflict are more ambiguous. Prominent findings in the literature (for instance Fearon and Laitin, 2003; Collier and Hoeffler, 2004; Hegre and Sambanis, 2006) suggest that poor countries with larger populations will be more likely to experience civil conflict. Using data from Gleditsch (2002), we find that Libya's real GDP in 2010 places it in the 40th percentile, and its population places it in the 43rd percentile. Thus, in 2010, Libya was somewhat poor, but not extremely so, and its population was somewhat smaller than the median state.

Finally, Libya's regime type in 2010 is somewhat unusual, in that it was a relatively coherent autocracy, with a combined polity score of -7, placing it in the 10th percentile (Marshall and Jaggers, 2002). Previous findings suggest that coherent autocracies and democracies should be at a lower risk of civil conflict onset, whereas mixed regime types should be at a higher risk (Hegre et al., 2001).

All told, indicators that has previously been found to systematically increase the risk of civil conflict onset suggest that according to most prominent indicators of the risk of civil conflict, Libya is a representative case of civil war in 2011. In the year prior to the onset of conflict, Libya was highly dependent on the production and export of oil, excluded a relatively large number of ethnic groups from power, was situated in an autocratic region with multiple ongoing civil conflicts, and was somewhat poorer than other states.

2 Data Description and Statistics

2.1 Event Data

To measure the US behavior toward the rebels and the government, the behavior of the Libyan government toward the rebels and the behavior of the rebels toward the Libyan government we do not rely on Twitter. Instead, we collect original data using news wires from Lexis Nexis and the software TABARI. Using newswires allows us to reduce the bias to reporting introduced by media fatigue and other forms of incentive-based media distortions that are more likely to affect articles from news outlets such as the New York Times or the CNN, as Schrodt, Gerner and Yilmaz (2004, 5-10) demonstrate.

To insure the integrity of the data, we omit any newswire report that relies exclusively or primarily on Twitter as a source of information. We also eliminate duplicate reports, so as to not have multiple records of the same event.

Data are coded using the CAMEO event ontology which includes twenty categories of events, ranging from "making public statements" to "engaging in unconventional mass violence." A detailed list of the events included can be found in Gerner et al. (2002). For an explanation of what event data is, see Schrodt (2012).

The data is recorded in the form of directed dyads: each action, in other words, is recorded as having an actor initiating it ("source") and an actor receiving it ("target"). For example, the US decision to use drone strikes against Gaddafi forces on April 23rd, 2011 is coded as having a source (the US) and a target (the Libyan government). This coding device allows us to carefully track changes in behavior from one actor to another, so as to answer the question: did the US become more cooperative toward the rebels?

The comprehensiveness of event data allows us to consider different facets of cooperation and conflict during the whole duration of the civil conflict. For example, when coding the behavior of the Libyan government toward the rebels, the data capture events as diverse as Gaddafi's brutal suppression of rebels forces (February 25th) and his offers of a ceasefire agreement (July 26th). Since the data records a wide array of foreign policy behaviors, in order to maintain the precision of the data it becomes important to distinguish not only whether an act is cooperative or conflictual, but also whether it entails, for instance, material or verbal cooperation. Therefore, we use the Goldstein (1992) scale to parse out events that might be similarly conflictual (or cooperative) but that might present different degrees of intensity of conflict (or cooperation). Consider, for example, the US condemnation of Gaddafi's protest repression on February 26 and the US authorization of drone strikes against Gaddafi forces on April 23rd. Both represent instances of hostile US behavior toward Gaddafi: yet in the first instance, the hostility manifested itself verbally, whereas in the second instance the hostility had immediate material reverberations—specifically, the use of military force. The Goldstein scale, through a continuous series of weights ranging from -10 (most conflictual) to +10 (more cooperative), allows us to include both events, while weighting them differently based on the intensity of the hostility or cooperation that they reflect. For a complete overview of the scale, see Goldstein (1992).

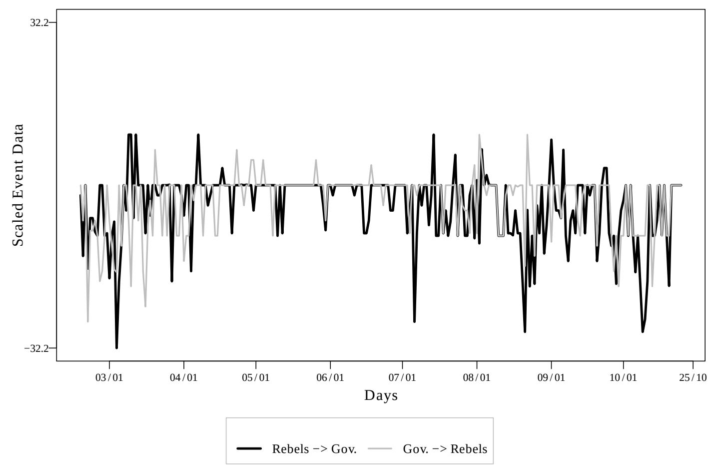
2.1.1 Examples

Table 2.1.1 reports some examples of events in our data set. *The examples are by no means exhaustive, as the dataset relies on more than 280 events in total.* Other, similar episodes took place throughout the conflict, but for the sake of parsimony, we present here only a few examples. To give a sense of the range of events contained in the dataset, the Table reports one example each of a very conflictual, very cooperative, and average behavior from an actor toward another, together with the exact date when that behavior took place. The data employs a "source->target" structure, where the source is the actor initiating the action and the target is the actor toward which the action is addressed. The table shows that the data is comprehensive and fine-grained, in that it measures very different forms of behavior, from pledging support to engaging in aerial bombings.

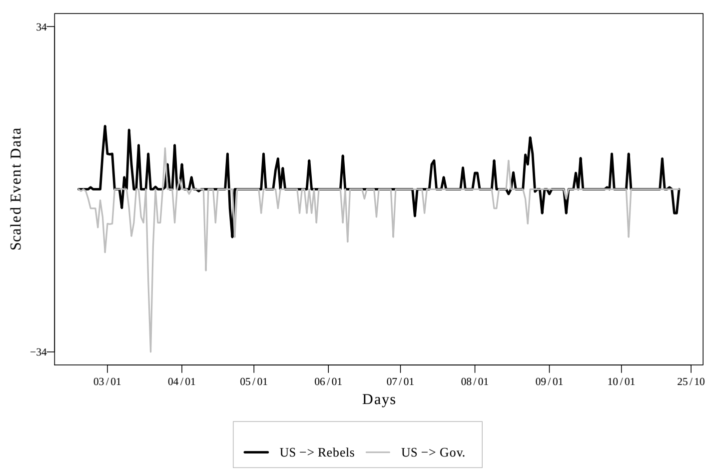
Figure 1 reports the time series of daily action of one actor (source) toward another (target), built using those event data. We illustrate the final product on Figure 1. The x-axis represents time (in days), and the y-axis represents the conflict (negative values) cooperation (positive values) continuum.[1] Negative weights represent conflictual actions and positive weights represent cooperative ones. We disaggregate the data to the daily level. For a detailed discussion of the scale, see Goldstein (1992). For similar uses of the scale in the modeling of event data, see, among others, Goldstein and Pevehouse (1997), Goldstein and Freeman (1990), and Goldstein et al. (2001).

[1]See Freeman (1989) and Shellman (2004) on temporal aggregation. When multiple events happen in one day, we sum the scaled value of all events in that day to generate a daily value for each series. Since conflictual events are assigned a negative value and cooperative ones are assigned a positive value, our data measure net cooperation between the actors of interest.

Figure 1: Time series of the event data tracking interactions between each of the actors in the Libyan civil war. The x-axis represents time (in days) and the y-axis represents scaled event data: values above zero represent net cooperative actions, and those below zero represent net conflictual actions.



(a) Libyan Rebels and Government.



(b) US Government and Libyan Rebels and Government.

Table 1: Examples of the event data collected. The format of the data is Source (the actor carrying on the action) ->Target (the actor toward which the action was carried), or directed dyad. To provide a parsimonious presentation of the data, the Table presents one example each from the most conflictual, the most cooperative, and the most common episode of behavior of each of the major actors toward the others recorded in our originally collected event data. The table also shows the main category to which that example belongs in the CAMEO ontology, together with the date when the event took place.

Interaction	Type of Event	CAMEO Event Category “Example” Date
US->Rebels	Most Frequent	Consider policy option “US officials said no option had been ruled out” 02/25/2011
	Most Conflictual	Undecided on Support ”US warns that [...] intervention to help opponents of Gaddafi would be ”controversial” 03/03/2011
	Most Cooperative	Cooperate militarily “US reaches an agreement with rebels on weapons” 08/23/2011
US->Government	Most Frequent	Demand change in leadership “US says Kadhafi must go” 04/21/2011
	Most Conflictual	Use aerial attacks ”The US extends air strikes in Libya” 04/04/2011
	Most Cooperative	Urges to Stop “The United States [..] called on [...] Gaddafi to stop 05/04/2011 attacking”
Rebels-> Government	Most Frequent	Fights with Arms “clashes between Libyan rebels and supporters of Gaddafi at the coastal hamlet of Bin Jawad” 03/07/2011
	Most Conflictual	Fights with Arms “Rebels drive back Kadhafi forces west of Misrata” 05/09/2011
	Most Cooperative	Retreats “Rebel fighters pulled back from the town of Ras Lanuf” 03/12/2011
Government-> Rebels	Most Frequent	Fights with Arms “Fierce clashes between pro- and anti-government forces” 02/24/2011
	Most Conflictual	Fights with Arms “Deadly clashes near [...] Benghazi with opposition”10/08/2011
	Most Cooperative	Asks for Ceasefire “Libyan government urges rebels for ceasefire” 08/18/2011

2.2 Twitter Data

To measure the impact of rebel diplomacy through Twitter, we collect original data on the Twitter activities of the primary rebel organization in the Libyan civil war, the NTC, which was active on Twitter from March 6 to August 6, 2011. We download and code *all of* the messages that were tweeted by this account during that period. We then create four different variables, following the four categories that we identify (publicizing international support, remarking battlefield success, denouncing government atrocities, and clarifying the rebels' aims). In coding these variables, we verify that different coders can reach the same conclusions (inter-coder reliability). We also run our models with one variable that simply counts the number of tweets through time, irrespective of the content of the tweet (see the article for the results).[2]

Figure 2 offers descriptive information on the type of the four different types of tweets issued by the NTC in the conflict, showing the number of tweets per category. The Twitter activity did not stop after President Obama authorized strikes against the Gaddafi forces in late March 2011. This pattern is consistent with what rebels said during interviews regarding trying to keep the support of the US through the intervention.[3] While we often treat foreign intervention as a dichotomous event—did the US intervene or not—based on some chosen threshold, a more detailed look at the events on the ground under analysis shows that the actors involved understand that foreign power's involvement is a complex phenomenon, which can take multiple forms (in this case, air bombing, condemnation of the government, aid to the rebels, etc.) whose consistency throughout the conflict is often needed for the rebels to win, but by no means guaranteed.[4]

The timing of the tweets depended on both the rebels' activities toward the government and on the US behavior, as revealed by a Granger causality test of the null hypothesis that the past values of actors' behaviors do not predict the Twitter activity. Taken together, these findings emphasize that Twitter was part of the rebels' broader strategy, both responding to events on the ground and responding to the US behavior toward the rebels. To circumvent the obstacles that the Gaddafi's regime had put on internet access, rebels had to devise a complex satellite system.[5]

2.2.1 Examples

Table 3 provides further examples of the tweets we code, and the full list will be released upon publication of the article. Because each Twitter variable in the models we present in the article represents a count of each type of Tweets, we standardize each of the series when including them in the VAR models. In the models, we do not impose any assumptions as to when these tweets should impact the US behavior—i.e., should their impact be immediate? Should they instead be lagged?. Instead, we test different model specifications (see homonymous section in the manuscript) and we triangulate through different tests to assess the one

[2]Note that there is also a fifth, residual category consisting of responses to individual messages sent to the NTC, updates about the status of the NTC website, messages indicating that a statement spanning multiple tweets is complete among other topics.

[3]Foss 2012, 52–60.

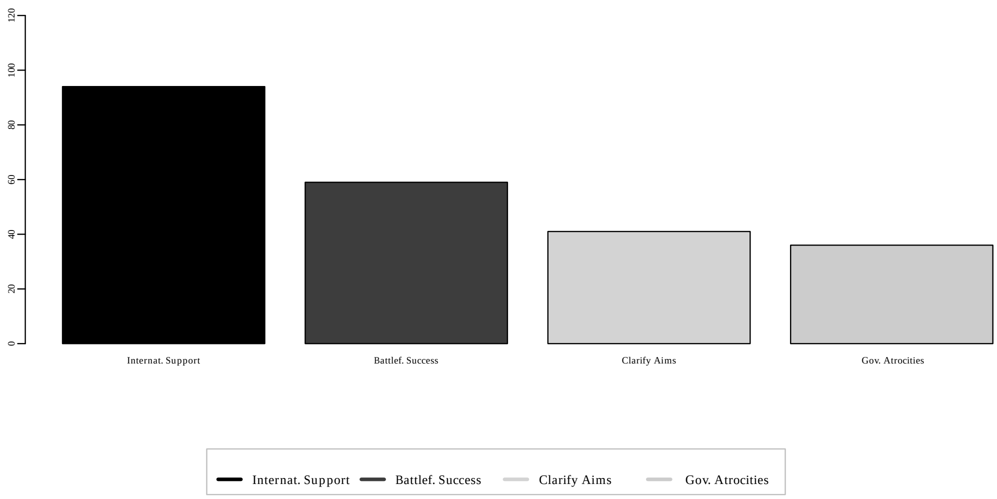
[4]See also Goldstein and Pevehouse 1997.

[5]CIWAG report 2011, p31.

Table 2: Granger Causality test for a VAR with four lags with five time series: the Libyan government's behavior toward the rebels, the rebels' behavior toward the government, the US behavior toward the rebels, the US behavior toward the rebels, and Twitter (irrespective of the type of Tweet). We report the subset of results for the effects of actors' behaviors on the Twitter activities.

	F-statistic	p-value
LibRebTOLibGov ->TwitterTOT	3.364	0.010
LibGovTOLibReb ->TwitterTOT	1.965	0.100
USGovTOLibReb ->TwitterTOT	2.505	0.042
USGovTOLibGov ->TwitterTOT	2.053	0.0877

Figure 2: Report of Libyan rebels' tweets, by type. The NTC also established a YouTube channel, "NTCLibya" and a Facebook profile, "National Transitional Council of Libya." Both were created later on in the conflict, on or after May 11th, 201, and neither of them appeared to be updated as frequently as the Twitter account.



that best represents the dynamics in the data.

Table 3: Examples of the tweets we coded from the NTC Twitter feed, by category.

Type of Signal	Sample Tweets
International Support	There will be cooperation between #Italy & #Libya in a number of different departments such as politics, security, & economics. #Feb17
	Catherine Ashton EU High Representative for Foreign Affairs & Security opens European Union office in Benghazi on Sunday. #Libya #Feb17
	The Council asked the UN to acceptance of Mr Shalegm as libya's representative at the international organisation #libya
Battlefield Success	NTC representatives have confirmed that #Sabha is breaking free from the Gaddafi regime's grip and provided the following details: #Libya
	Misrata has defeated Qadfi army, 11African mercenaries were killed, 5 at least arrested, videos & pics later viva #libya
	to our people in Misrata & Zawai we all with u, we'll fight to the last blood drop to safe u, we will win #libya
Clarify Aims & Beliefs	TNC regard terrorism as one of the most serious threats to international peace and security #LIBYA
	our goal is to bring freedom, Justice and democracy to #libya
	The Council is committed to the equal opportunities between men and women and the promotion of women empowerment #libya
Publicize Government Atrocities	#Sabah Two demonstrators were shot and were transported to the March 2nd Hospital, before being kidnapped by Gaddafi troops. #Libya #NTC
	NTC denounces the Gaddafi regime for the use of child soldiers
	Confirmed by eyewitness in #Tripoli: Gaddafi forces R using surface to surface rockets to shell houses in Tripoli after #NATO airstrikes..

3 VAR Model Specification

As we state in the manuscript, we choose the VAR model that best fits the data—that is, the model that best captures the true dynamics characterizing the interactions between rebels, the government, and the US. To this end, for each type of Twitter message (5 in total) we estimate 15 different models, systematically increasing the number of lags p from 1 to 15. Put differently, we compare the fit of models for which the effects of an event in the system of interactions between rebels, the government, and the US is felt for the next p days, where p goes from 1 to 15.

Then, in order to select the correct lag length among these 15 models for each Twitter type, we balance the two desirable properties of VAR and of statistical models in general: accuracy and parsimony. In other words, we want to include enough lags to correctly model the dynamics on the ground (accuracy) while avoiding including so many lags that the model is over-fitted and thus inefficient (parsimony).[6] We thus triangulate between multiple statistics, using information criteria AIC and BIC, as well as likelihood ratio tests and Lagrange multiplier (LM) test for autocorrelation in the residuals.[7]

The chi-squared test compares models on the basis of a likelihood ratio test, testing the null hypothesis of whether the VAR with p lags should have p lags against the null that it should have $p + 1$ lags. The AIC, but especially BIC, statistics, in turn, also look at the number of parameters, a feature that allows us to penalize models that are not parsimonious. Finally, the Lagrange multiplier test for autocorrelation in the residuals makes it possible to test whether the number of lags included in the main model is enough to capture all the temporal dynamics that characterize the data—in other words, it allows us to check that there are no omitted lags that bias the results.[8]

Adopting this approach to model selection allows us to find the best model without making *a priori* assumptions as to the length of the effect of single events or Tweets on the way in which interactions between the rebels, the government, and the US unfolded. In other words, we experiment with different durations of the effects of Tweets and we select the one that best reflects the actual dynamics in the data.

We report the relevant statistics for the 15 model specifications for each of the five models that we estimate. In other words, we design one model for each of the four tweets types we identify, and then one more model where all the tweets are measured together in the same variable; we then specify each of these five models in 15 ways, and we then report the statistics for these models.

When incorporating a time series that measures all the Twitter messages, irrespective of the message publicized, the model that best fits the data (that is, the model that is accurate and includes all the relevant lags but that is also parsimonious and only includes the relevant lags) is a model with four lags. Albeit the information criteria that penalizes the most for every additional lag, the BIC, indicates that the most parsimonious model is a model with only 1 lag, the significant chi-squared test for the likelihood ratio test shows that a model with just one lag fails to capture the action-reaction dynamics on the ground (p=0.000), and that more lags are necessary to this end (see Table 4). The Lagrange multiplier (LM) test for autocorrelation

[6] Brandt and Williams 2007, 25–27.
[7] Brandt and Williams 2007, 25–27.
[8] Brandt and Williams 2007, 25–27, Enders 2008.

in the residuals only fails to reject the null hypothesis of no autocorrelation within the residuals when four lags are included in the main model (χ^2=29.9634, p-value=0.225). The results of the LM test indicate therefore that only a model with four lags captures all the temporal dynamics that characterize the data while maintaining parsimony, we estimate a model with four lags. Our results are robust to the inclusion of more than four lags, though those models are inefficient.

When incorporating a time series with the Twitter messages that publicize international support, the model that best fits the data (that is, the model that is accurate and includes all the relevant lags but that is also parsimonious and only includes the relevant lags) is a model with four lags. Again, the BIC indicates that the most parsimonious model is a model with only one lag (see Table 5), but the Lagrange multiplier (LM) test for autocorrelation in the residuals only fails to reject the null hypothesis of no autocorrelation in the residuals after four lags have been added to the main model (χ^2=28.1934, p-value=0.299). We also find that introducing more than four lags is inefficient, but does not change our results.

When incorporating a time series with the Twitter messages that publicize battlefield success, the model that best fits the data (that is, the model that is accurate and includes all the relevant lags but that is also parsimonious and only includes the relevant lags) is a model with four lags. Albeit the information criteria that penalizes the most for every additional lag, the BIC, indicates that the most parsimonious model is a model with only one lag, and the chi-squared test lends support to this proposition (p=0.144) (see Table 6), the Lagrange multiplier (LM) test for autocorrelation in the residuals only fails to reject the null hypothesis of no autocorrelation in the residuals after four lags have been added to the main model (χ^2=21.1228, p-value=0.685). Therefore, we estimate a model with four lags, so as to avoid omitting lags from the mail model. Introducing more than four lags is inefficient, but does not change our results.

When incorporating a time series with the Twitter messages that clarifies rebels' aims, the model that best fits the data (that is, the model that is accurate and includes all the relevant lags but that is also parsimonious and only includes the relevant lags) is a model with 4 lags. Albeit the information criteria that penalizes the most for every additional lag, the BIC, indicates that the most parsimonious model is a model with only 1 lag, and the chi-squared test lends support to this proposition (p=0.167) (see Table 7), the Lagrange multiplier (LM) test for autocorrelation in the residuals only fails to reject the null hypothesis of no autocorrelation in the residuals after four lags have been added to the main model (χ^2=26.480, p-value=0.382). Therefore, we estimate a model with four lags, so as to avoid omitting lags from the mail model. Introducing more than four lags is inefficient, but does not change our results.

When incorporating a time series with the Twitter messages that denounces the government's atrocities, the model that best fits the data (that is, the model that is accurate and includes all the relevant lags but that is also parsimonious and only includes the relevant lags) is a model with 4 lags. Albeit the information criteria that penalizes the most for every additional lag, the BIC, indicates that the most parsimonious model is a model with only 1 lag, the significant chi-squared test shows that a model with just one lag fails to capture the action-reaction dynamics on the ground (p-value=0.057), and that more lags are necessary (see Table 7). The Lagrange multiplier (LM) test for autocorrelation in the residuals only fails to reject the null hypothesis of no autocorrelation within the residuals when four lags are included in the main model (χ^2=23.8779, p-value=0.5264). The results of the LM test indicate therefore that only a model with four lags captures all the temporal dynamics that characterize the data while maintaining parsimony, we estimate a model with four lags. Our results are robust to the inclusion of more than four lags, though those models are inefficient.

Table 4: Lag length specification tests for a model of the interactions between the Libyan government, the rebels, and the US, plus a time series of all the tweets, irrespective of the type.

Lags	AIC	BIC	χ^2	p-value
1	11.281	11.722	0.000	0.000
2	11.328	12.135	37.177	0.056
3	11.328	12.502	46.605	0.005
4	11.331	12.872	44.850	0.009
5	11.393	13.301	31.589	0.170
6	11.376	13.651	46.917	0.005
7	11.444	14.086	28.625	0.280
8	11.514	14.523	27.674	0.323
9	11.496	14.872	43.713	0.012
10	11.604	15.347	19.184	0.788
11	11.698	15.808	21.227	0.680
12	11.689	16.165	38.731	0.039
13	11.502	16.346	67.731	0.00001
14	11.492	16.702	36.687	0.062
15	11.489	17.066	34.339	0.101

Table 5: Lag length specification tests for a model of the interactions between the Libyan government, the rebels, and the US, plus a time series of all the tweets that publicize international support.

Lags	AIC	BIC	χ^2	p-value
1	11.318	11.759	0.000	0.000
2	11.381	12.188	33.709	0.114
3	11.412	12.587	39.585	0.032
4	11.535	13.077	19.120	0.791
5	11.618	13.526	27.094	0.351
6	11.634	13.909	40.215	0.028
7	11.708	14.350	27.584	0.327
8	11.761	14.770	31.007	0.189
9	11.754	15.130	41.559	0.020
10	11.880	15.623	15.861	0.919
11	11.983	16.093	19.577	0.769
12	12.094	16.571	17.639	0.857
13	12.050	16.894	43.475	0.012
14	12.058	17.269	33.672	0.115
15	12.086	17.664	29.367	0.249

Table 6: Lag length specification tests for a model of the interactions between the Libyan government, the rebels, and the US, plus a time series of all the tweets that publicize battlefield success.

Lags	AIC	BIC	χ^2	p-value
1	11.319	11.760	0.000	0.000
2	11.387	12.194	32.518	0.144
3	11.443	12.617	34.216	0.103
4	11.510	13.051	31.131	0.185
5	11.614	13.522	22.799	0.589
6	11.613	13.888	43.583	0.012
7	11.694	14.336	26.110	0.402
8	11.777	14.786	25.151	0.454
9	11.791	15.167	37.536	0.051
10	11.925	15.667	14.542	0.951
11	12.036	16.146	18.026	0.841
12	12.126	16.602	21.391	0.671
13	12.090	16.934	42.063	0.018
14	12.134	17.344	27.823	0.316
15	12.149	17.727	31.402	0.176

Table 7: Lag length specification tests for a model of the interactions between the Libyan government, the rebels, and the US, plus a time series of all the tweets that clarify the rebels' aims.

Lags	AIC	BIC	χ^2	p-value
1	11.296	11.736	0.000	0.000
2	11.367	12.174	31.685	0.167
3	11.407	12.581	37.736	0.049
4	11.421	12.962	42.508	0.016
5	11.508	13.416	26.263	0.394
6	11.499	13.774	45.257	0.008
7	11.552	14.194	31.761	0.165
8	11.616	14.625	28.831	0.271
9	11.613	14.989	40.805	0.024
10	11.705	15.448	22.209	0.624
11	11.826	15.935	16.442	0.901
12	11.860	16.337	31.024	0.188
13	11.794	16.638	47.234	0.005
14	11.808	17.019	32.627	0.141
15	11.845	17.422	28.094	0.304

Table 8: Lag length specification tests for a model of the interactions between the Libyan government, the rebels, and the US, plus a time series of all the tweets that expose governments' atrocities

Lags	AIC	BIC	χ^2	p-value
1	11.304	11.744	0.000	0.000
2	11.351	12.158	37.031	0.057
3	11.361	12.535	44.546	0.009
4	11.448	12.989	26.744	0.369
5	11.536	13.444	26.010	0.407
6	11.590	13.865	32.348	0.148
7	11.623	14.265	35.829	0.074
8	11.706	14.715	25.113	0.456
9	11.657	15.033	49.564	0.002
10	11.779	15.522	16.637	0.895
11	11.806	15.916	33.253	0.125
12	11.850	16.327	29.322	0.251
13	11.737	16.580	55.332	0.0004
14	11.741	16.951	34.245	0.103
15	11.803	17.381	23.939	0.523

4 Further Results

4.1 Twitter's Impact on Rebel-Government relations

We do not find a significant effect of Twitter on the interactions between rebels and government, which provides additional evidence to the claim that the Twitter account was used as a tool of public diplomacy to attract the attention (and the support) of foreign actors.

4.2 Further VAR Results from the Manuscript

Figure 1 in the article represents the effect of Twitter on US behavior toward the rebels on the fourth day after it was tweeted, which represents the first day in which the tweets are significant for those cases that reach significance at the 95% level. In Figure 3 we plot the full timeline of the effect of each of the four types of Twitter discussed in the paper on the US behavior toward the rebels, tracing their effect for several days. In other words, each plot in Figure 3 reports the result of the effect of the Twitter feed on US behavior toward the rebels for the a model with each type of Tweeter message, tracing that same result through several days.

Figure 3 shows that, as we discuss in the article, on average, the effect of Twitter as a tool of rebel diplomacy is not immediate, manifesting itself instead after four or five days. Moreover, as Figure 2 in the manuscript shows, the substantive impact of Twitter grows as days pass. Taken together, the findings that it takes tweets a few days to start impacting the US behavior toward the rebels and that their effect grows with time provide further evidence that the mechanism through which diplomacy via Twitter impacts US behavior toward the rebels is by impacting the image of the conflict in the US, rather than a more immediate mechanism, such as the provision of battlefield information. At the same time, the prompt time frame with which Twitter affected the US behavior reflects the accelerated time frame that characterized the decision-making regarding the Libyan civil war in the US—an accelerated time frame that spurred a momentous debate on the proper timing of force authorization and on legacy of the 1973 War Powers Act more broadly.[9]

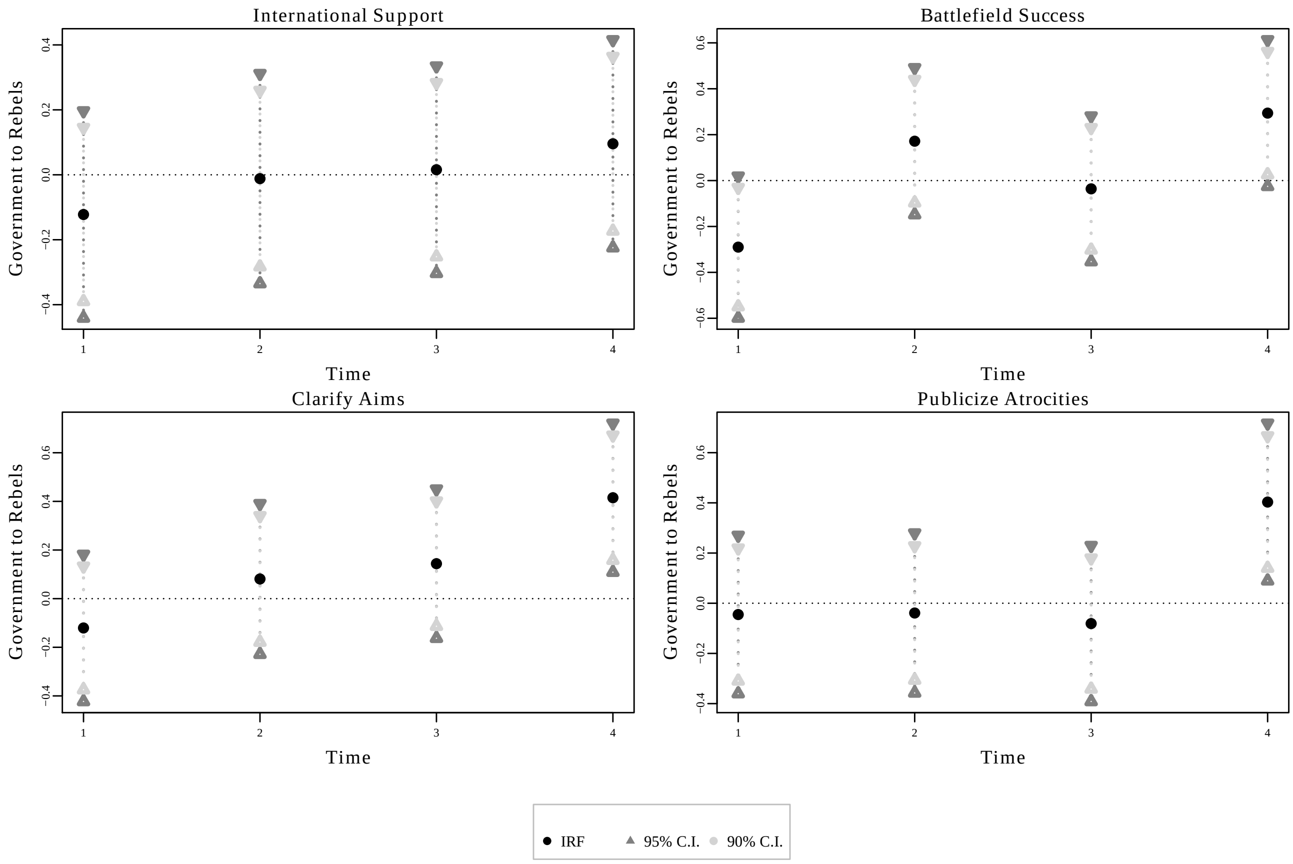
5 Robustness Checks

Finally, Figures 4 and 5 presents the results of the robustness checks reported in the paper.

In Figure 4, we control for whether the impact of rebel diplomacy via Twitter is robust when we also control for other forms of communication between the rebels and the US. Thus, we re-estimate the VAR model from the paper, with all the time series of the actors' behaviors that we include in the main model: the rebels' actions toward the Libyan government; the Libyan government's actions toward the rebels; the US government's actions toward the rebels; the US government's actions toward the Libyan government; and each of the four types of tweets that we identify in our previous section. We then include an additional series to this model: the actions on the part of the rebels toward the US. This series includes forms of traditional diplomacy, and thus events such as the meeting in Instambul between NTC and US representatives on July 2011. Incorporating this series allows us to control for whether the positive

[9]"Letter from the President regarding the commencement of operations in Libya" The White House Press Release, 03/21/2011. "Speaker Boehner Letter to President Obama on Military Action in Libya." Speaker Press Release, 03/22/2011.

Figure 3: IRF graphs for a VAR model, which show the impact on the US behavior toward the rebels of a positive, one standard deviation increase in the number of each of the different tweets, over several days, for each of the Twitter categories.



and significant effect of Twitter is robust to the inclusion of traditional channels of diplomacy between the rebels and the US.

Figure 4 plots the resulting IRFs from this model. As with Figure 1 in the article, the black dots within each plot in Figure 4 answer the question: if the rebels tweet a specific message, does US behavior toward the rebels become more cooperative (positive values), more conflictual (negative values), or remain unchanged (zero values) in the next week? As can be seen, even when controlling for traditional form of diplomacy on the part of the rebels toward the US, tweets that clarify the aims of the rebels (Figure 4(c)) and that publicize government atrocities (Figure 4(d)) significantly increase the level of cooperation from the US toward the rebels. The fact that Twitter in an effective tool of diplomacy, even when controlling for more traditional forms of diplomacy, shows that Twitter plays a specific and crucial role in the diplomatic effort of the rebels, as we discuss at length in the article: to overcome the government's privileged access to the media, and to engage foreign audiences in a public fashion. It was, in other words, a form of "public diplomacy."

In Figure 5 we also control for the interactions of the US with its NATO allies. In other words, we include two additional series to the model: the US actions toward its NATO allies, and the actions of the NATO allies toward the US. Examples of these interactions are the emergency meeting called by NATO Secretary General Anders Fogh Rasmussen to discuss the Libyan situation (February 25) and the US appeal to its NATO allies to step up their contribution to the mission (June 10).

These series allow us to capture the degree to which the US actions toward the Libyan rebels depended on the interactions within the alliance, and to control for whether the impact of rebel diplomacy via Twitter on US behavior toward the rebels is still significant. Figure 5 reports the results from this model. As with Figure 1 in the article, the black dots within each plot in Figure 5 answer the question: if the rebels tweet a specific message, does US behavior toward the rebels become more cooperative (positive values), more conflictual (negative values), or remain unchanged (zero values) in the next week? Even when controlling for the interactions within NATO, tweets that clarify the aims of the rebels (Figure 5(c)) and that publicize government atrocities (Figure 5(d)) significantly increase the level of cooperation from the US toward the rebels. The scarce impact in the model of NATO interactions resonates with events on the ground: while the alliance strived to acquire a key role in the conflict, it heavily relied on US military supplies and logistics, so much so that Secretary of Defense Gates and Secretary of Defense Panetta emphasized the exasperation of the US with the lack of burden sharing in the alliance. In the words of NATO Secretary General Anders Fogh Rasmussen:[10]

> For the first time in the history of NATO, we see a NATO operation not led by the Americans but led by the Europeans.[...]But it's a fact we could not carry out this operation without the unique and critical assets provided by the United States [...] So we are still dependent on America.[11]

[10]"Gates rebukes NATO allies, warns of 'dismal' future" AFP, 06/10/2011.
[11]"Libya exposes Europe's reliance on US power: NATO chief", AFP,07/14/2011.

Figure 4: IRF graphs for VAR models, which show the impact of a one standard deviation increase in the number of each type of tweet on the US behavior toward the rebels 4 days after the increase in Twitter usage occurs. The models contain the same series as the one in the model presented in the article, while also controlling for traditional forms of diplomacy.

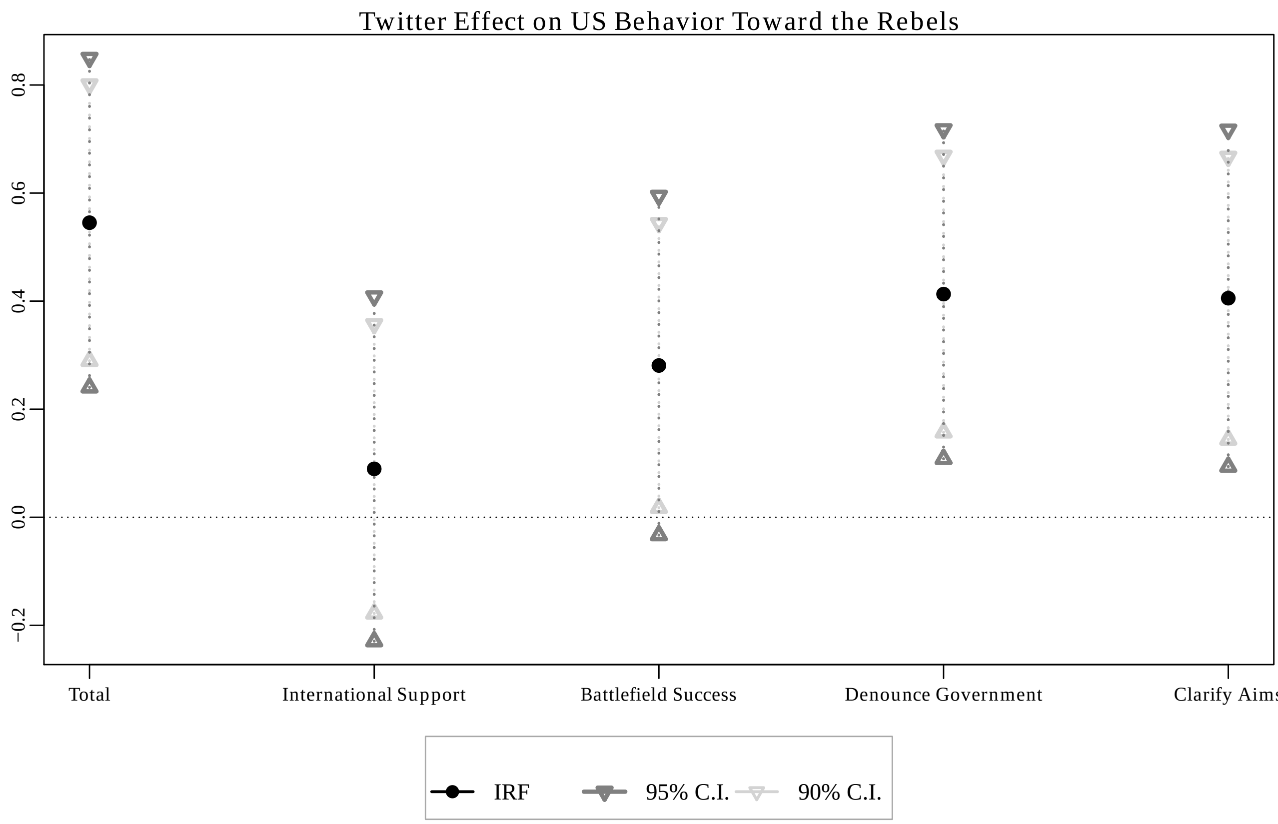


Figure 5: IRF graphs for VAR models, which show the impact of a one standard deviation increase in the number of each type of tweet on the US behavior toward the rebels 4 days after the increase in Twitter usage occurs. The models contain the same series as the one in the model presented in the article, while also controlling for the interactions between the US and its NATO allies.

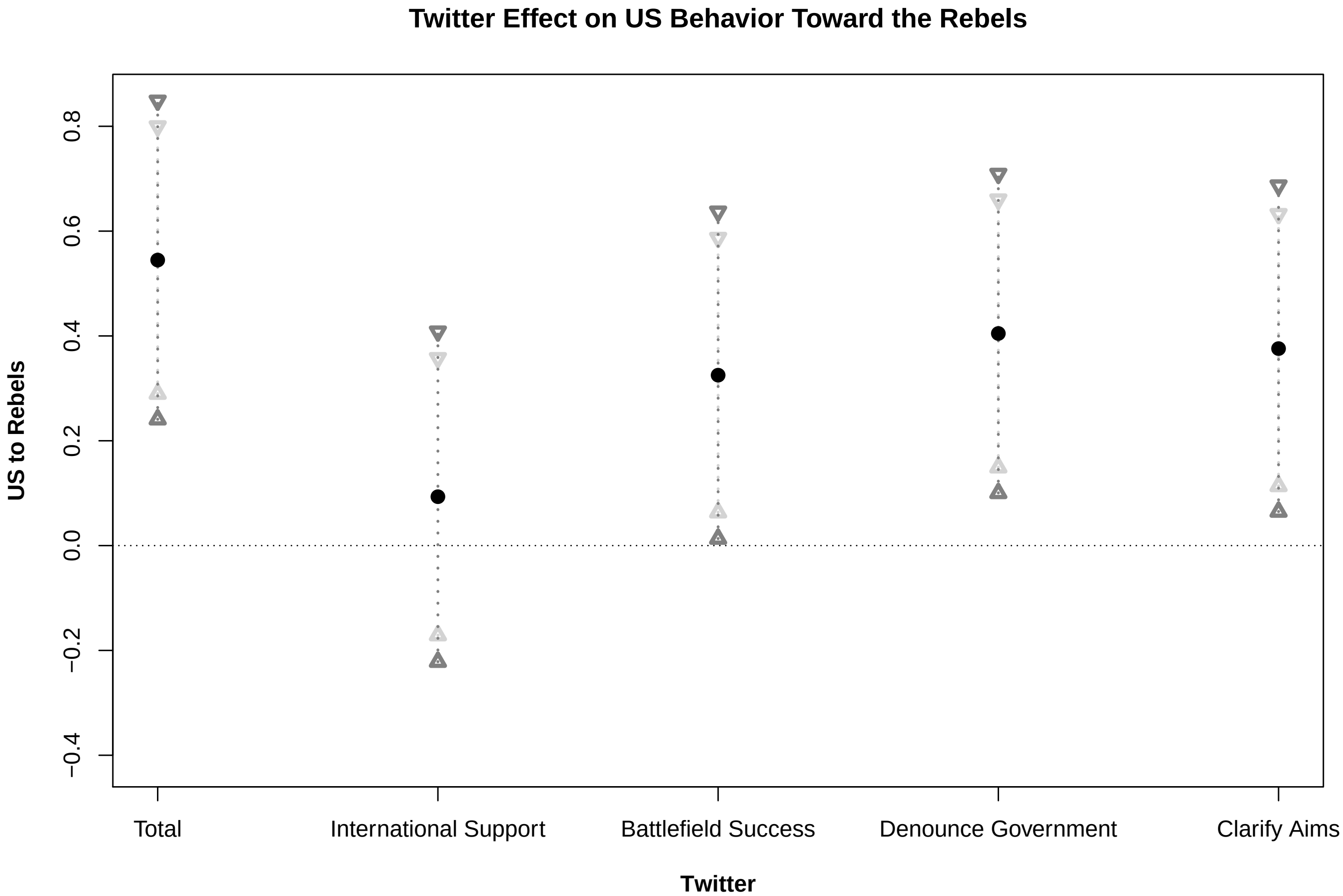
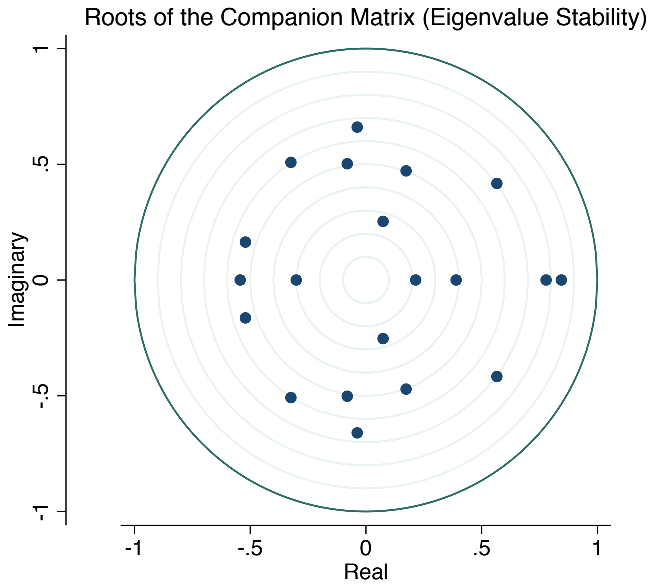


Figure 6: Graph of the eigenvalues indicating that these eigenvalues are well inside the unit circle, and thus that the model presents covariance stationarity.



6 Post-Estimation Statistics

We perform tests to assess the feasibility of our model (Hamilton, 1994). For the sake of a more parsimonious Appendix, we present the results for the VAR(4) model with the Tweet category of reporting government atrocities, and we share our code and results for all the models in our Replication File. We further test for autocorrelation in the residuals with a Lagrange multiplier test (LM) and we find that there is none (test statistics= 8282.66, p-value= 0.00). We establish the covariance stationarity by testing the eigenvalue stability condition of the VAR model (see Figure 6).

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