How Saudi Crackdowns Fail to Silence Online Dissent
Online Appendix

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Abstract

Activists, religious leaders, and journalists in Saudi Arabia have been imprisoned and even tortured for online dissent. This reflects a growing trend worldwide in the use of physical repression to censor online speech. In this paper, we examine the political imprisonment of well-known Saudis to provide the first large-scale, systematic study of the effects of offline repression on online dissent. Analyzing over 300 million tweets and Google search data from 2010 to 2017 using automated text analysis and crowd-sourced human evaluation of content, we find that although repression deterred imprisoned Saudis from continuing to dissent online, it did not suppress dissent overall. Observing repression increased dissent—including criticisms of the ruling family and calls for regime change—among the followers of those who were imprisoned, and drew public attention to arrested Saudis and their causes. Other prominent figures were not deterred by the repression of their peers and continued to dissent online.

Keywords: repression; social media; online mobilization; censorship; Saudi Arabia

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A Descriptive Data

Table A1: Imprisoned Opinion Leaders

	Name	Type	Official Arrest Reason	Unofficial Arrest Reason
1	Bandar al-Nogaithan	Judicial Reform	Disobeying ruler / Slandering judiciary	Tweets critical of judiciary
2	Abdulrahman al-Subaihi	Judicial Reform	Disobeying ruler / Slandering judiciary	Tweets critical of judiciary
3	Abdulrahman Al-Rumaih	Judicial Reform	Disobeying ruler / Slandering judiciary	Tweets critical of judiciary
4	Raif Badawi	Liberal	Apostosy /Insulting Islam / Violating Anti-Cyber Crime Law	Comments on his website debating political and religious issues in KSA
5	Omar al-Saeed	Liberal	Harming public order / Setting up unliscensed organization	Calling for Democracy/Criticizing Saudi HR Record
6	Abdullah al Hamid	Liberal	Sowing Discord and Chaos/Violating Public Safety	Calling for Prison reform / resignation of Interior Minister
7	Issa al-Nukheifi	Liberal	Disobedience to the ruler/ Violating cybercrimes law	Accused authorities of corruption / human rights violations
8	Abdulaziz al-Hussan	Liberal	Providing inaccurate information about the government	Representing arrested lawyers / tweeting about their trial
9	Mohammed al-Bajady	Liberal	Establishing HR Org/ Distorting state's reputation / Impugning judicial independence / instigating relatives of detainees to protest / Possessing censored books	Organized protest against arbitrary detention
10	Abdulkarim Al-Khoder	Liberal	Disobeying the ruler / Inciting disorder / Harming the image of the state / Founding an unlicensed organization	Crackdown on Saudi Civil and Political Rights Association
11	Fowzan al-Harbi	Liberal	Inciting disobedience to the ruler / Describing KSA as a 'police state'	Crackdown on Saudi Civil and Political Rights Association
12	Khaled al-Johani	Liberal	Being present at a prohibited demonstration/ Distorting the kingdom's reputation/ Contact with known Saudi dissident abroad	Participated in 'Day of Rage' and spoke to international journalists
13	Mohammad Fahad al-Qahtani	Liberal	Sowing discord / Disturbing public order / Breaking allegiance with the ruler	Calling for Prison reform / resignation of Interior Minister
14	Suliman al-Rashoodi	Liberal	Breaking Allegiance with Ruler / Attempting to distort reputation of kingdom	Arrested for Publication 'The Legitimacy of Demonstrations in Islamic Law'
15	Saleh al-Ashwan	Liberal	Breaking allegiance to and disobeying the ruler/ Questioning the integrity of officials/ Member of unliscensed organization	Crackdown on SCPRA / Drew attention to Saudi prisoners in Iraq
16	Waleed Abul Khair	Liberal	Disobeying the ruler and seeking to remove his legitimacy/ Insulting the judiciary and questioning the integrity of judges / Setting up an unlicensed organization / Harming the reputation of the state	Establishing human rights organization / criticizing Saudi HR record
17	Zuhair Kutbi	Liberal	Sowing discord/ Inciting public opinion /Reducing the government's prestige	Calling for Constitutional Monarchy / Combattting Repression on TV
18	Alaa Brinji	Liberal	Insulting rulers / Inciting public opinion	Critical tweets about imprisonment of activists and ending the driving ban
19	Hamza Kashagri	Liberal	Apostosy/ Crossing red lines / Denigrating religious beliefs in God and His Prophet	Popular calls for his death online following tweets humanizing Prophet
20	Turki al-Hamad	Liberal	No public charges	Tweets criticizing Saudi interpretation of Islam
21	Hassan Farhan Al-Malki	Moderate Cleric	Supporting proximity among Islamic sects	Defending Shia rights surrounding Nimr al-Nimr's arrest
22	Abdulaziz al-Tarifi	Sahwa Cleric	Calling for Constitutional Monarchy	Tweet criticizing monarchy for religious police reform / kowtowing to West
23	Mohammad al-Arefe	Sahwa Cleric	No public charges	Supporting Morsi / Muslim Brotherhood / Criticizing Saudi Hajj Trains
24	Mohsen al-Awaji	Sahwa Cleric	No public charges	Supporting Morsi /Muslim Brotherhood/ Signing Communique
25	Ibrahim al-Sakran	Salafi Cleric	Damaging fabric of society / Inciting public opinon / Interefering in international affairs	Tweets criticizing foreign policy in Yemen / treatment of detainees
26	Adel Ali al-Labbad	Shia Activist	Disobedience to Ruler/Disturbing Public Order	Poems criticizing arrests / treatment of dissidents
27	Mohamed Baqir al-Nimr	Shia Activist	No public charges	Tweeting about Nimr al Nimr's trial
28	Ahmed al-Musheikhis	Shia Activist	No public charges	Protesting Detentions / Advocating Shia Rights / Belonging to unregistered HR org.
29	Nimr al-Nimr	Shia Cleric	Disturbing security /Seeking Foreign Meddling /Terrorism	Giving anti-regime speeches/ Defending political prisoners / Inciting Protest
30	Tawfiq al-Amer	Shia Cleric	Defaming ruling system /Ridiculing religious leaders/ Inciting sectarianism/ Calling for change/ Disobeying the ruler	Criticizing treatment of Shia / Calling for reforms
31	Sahar Al-Khashrami	Anti-University Corruption	Defamation / Violating Anti-Cyber Crime Law	Hashtag campaign condemning academic fraud, forgery and plagiarism
32	Lujain al-Hathloul	Women's Rights	Tried under vague provisions of anti-cybercrime law	Comments on social media calling for end to driving ban / guardianship
33	Manal al-Sharif	Women's Rights	Disturbing public order / Inciting Public Opinion	Social media campaigns calling for protests / filming her violation of driving ban
34	Mayasa al-Amoudi	Women's Rights	Tried under vague provisions of anti-cybercrime law	Comments on social media calling for end to driving ban / guardianship
35	Samar Badawi	Women's Rights	No public charges	Women's Driving Campaign / Managing jailed husband's Twitter account
36	Souad al-Shammari	Women's Rights	Insulting Islam / Inciting rebellion	Women's Driving Campaign / Critcizing Guardianship System

Table A2: Opinion Leader Arrest Dates (First Arrest)

	Name	Type	First Arrest Date	First Release Date
1	Bandar al-Nogaithan	Judicial Reform	10/27/14	4/15/15
2	Abdulrahman al-Subaihi	Judicial Reform	10/27/14	5/15/15
3	Abdulrahman Al-Rumaih	Judicial Reform	10/27/14	4/15/15
4	Raif Badawi	Liberal	6/17/12	not released
5	Omar al-Saeed	Liberal	4/30/13	12/24/15
6	Abdullah al Hamid	Liberal	9/2/12	not released
7	Issa al-Nukheifi	Liberal	9/1/12	4/6/16
8	Abdulaziz al-Hussan	Liberal	3/11/13	3/12/13
9	Mohammed al-Bajady	Liberal	3/21/11	8/6/13
10	Abdulkarim Al-Khoder	Liberal	6/28/13	not released
11	Fowzan al-Harbi	Liberal	12/26/13	6/24/14
12	Khaled al-Johani	Liberal	3/1/11	8/6/12
13	Mohammad Fahad al-Qahtani	Liberal	3/9/13	not released
14	Suliman al-Rashoodi	Liberal	12/12/12	12/12/17
15	Saleh al-Ashwan	Liberal	7/7/12	not released
16	Waleed Abul Khair	Liberal	4/15/14	not released
17	Zuhair Kutbi	Liberal	7/15/15	not released
18	Alaa Brinji	Liberal	5/12/14	not released
19	Hamza Kashagri	Liberal	2/7/12	10/29/13
20	Turki al-Hamad	Liberal	12/24/12	6/5/13
21	Hassan Farhan Al-Malki	Moderate Cleric	10/14/14	12/24/14
22	Abdulaziz al-Tarifi	Sahwa Cleric	4/25/16	not released
23	Mohammad al-Arefe	Sahwa Cleric	7/20/13	7/22/13
24	Mohsen al-Awaji	Sahwa Cleric	7/20/13	7/22/13
25	Ibrahim al-Sakran	Salafi Cleric	6/14/16	not released
26	Adel Ali al-Labbad	Shia Activist	10/10/12	not released
27	Mohamed Baqir al-Nimr	Shia Activist	10/15/14	11/1/14
28	Ahmed al-Musheikhis	Shia Activist	1/5/17	not released
29	Nimr al-Nimr	Shia Cleric	7/8/12	executed 1/2/2016
30	Tawfiq al-Amer	Shia Cleric	2/27/11	3/6/11
31	Sahar Al-Khashrami	University Corruption	4/15/15	4/15/15
32	Lujain al-Hathloul	Women's Rights	12/2/14	2/3/15
33	Manal al-Sharif	Women's Rights	5/21/11	5/30/11
34	Mayasa al-Amoudi	Women's Rights	12/2/14	2/3/15
35	Samar Badawi	Women's Rights	1/1/16	1/13/16
36	Souad al-Shammari	Women's Rights	10/28/14	1/28/15

Those who are "not released" were not yet released at the time of our data collection in January 2017.

Table A3: Imprisoned Opinion Leaders and Non-Imprisoned “Match” Opinion Leaders

	Name	Twitter Handle	Imprisoned	Match	Type	Followers Count
1	Omar al-Saeed	181Umar	imprisoned	Abdullah al-Nasri	Liberal	2497
2	Abdulaziz al-Tarifi	abdulaziztarefe	imprisoned	Suhail bin Mualla al-Mutairi	Sahwa Cleric	1029931
3	Suhail bin Mualla al-Mutairi	aborazan2011	match		Sunni Cleric	126755
4	Abdullah al Hamid	Abubelal_1951	imprisoned	Abdullah al-Nasri	Liberal	83609
5	Adel Ali al-Labbad	adel_lobad	imprisoned	Saeed Abbas	Shia Activist	7140
6	Issa al-Nukheifi	aesa_al_nukhifi	imprisoned	Mujtahidd	Liberal	26549
7	Abdulaziz al-Hussan	Ahussan	imprisoned	Abdullah al-Nasri	Liberal	41966
8	Mohammed al-Bajady	albgadi	imprisoned	Waleed Sulais	Liberal	23482
9	Alaa Brinji	albrinji	imprisoned	Waleed Sulais	Liberal	1448
10	Abdullah al-Nasri	alnasri1	match		Judicial Reform	18307
11	Abbas Said	alsaeedabbas	match		Shia Cleric	11892
12	Abdulrahman al-Subaihi	Alsubaihiabdul	imprisoned	Abdullah al-Nasri	Judicial Reform	38067
13	Abdullah Rahman al-Sudais	assdais	match		Sunni Cleric	315890
14	Abdulkarim Al-Khoder	drkhdar	imprisoned	Waleed Sulais	Liberal	38400
15	Sadeq al-Jibran	DrSadeqMohamed	match		Judicial Reform	16913
16	Fowzan al-Harbi	fowzanm	imprisoned	Waleed Sulais	Liberal	2611
17	Hala al-Dosari	Hala_Aldosari	match		Women’s Rights	57010
18	Hamza Kashagri	Hmzmz	imprisoned	Rashad Hassan	Liberal	18917
19	Hassan Farhan Al-Malki	HsnFrhanALmalki	imprisoned	Abdullah Rahman al-Sudais	Moderate Cleric	309260
20	Ibrahim al-Sakran	iosakran	imprisoned	Abdullah Rahman al-Sudais	Salafi Cleric	237899
21	Khaled al-Johani	KhaledLary	imprisoned	Mujtahidd	Liberal	4401
22	Abdulrahman Al-Rumaih	LawyerAMRumaih	imprisoned	Sadeq al-Jibran	Judicial Reform	8970
23	Lujain al-Hathloul	LoujainHathloul	imprisoned	Hala al-Dosari	Women’s Rights	307382
24	Mohamad Ali Mahmoud	ma573573	match		Liberal Writer	51322
25	Manal al-Sharif	manal_alsharif	imprisoned	Hala al-Dosari	Women’s Rights	275666
26	Mayasa al-Amoudi	maysaaX	imprisoned	Hala al-Dosari	Women’s Rights	202147
27	Mohamed Baqir al-Nimr	mbanalnemer	imprisoned	Saeed Abbas	Shia Activist	43483
28	Mohammad Fahad al-Qahtani	MFQahtani	imprisoned	Waleed Sulais	Liberal	81054
29	Mohammad al-Arefe	MohamadAlarefe	imprisoned	Abdullah Rahman al-Sudais	Sahwa Cleric	21325719
30	Mohsen al-Awaji	MohsenAlAwajy	imprisoned	Yousef Ahmed Qasem	Sahwa Cleric	1624072
31	Ahmed al-Musheikhis	mshikhs	imprisoned	Saeed Abbas	Shia Activist	2158
32	mujtahid	mujtahidd	match		Liberal Regime Critic	2082608
33	Fawaz al-Ruwaili	Muwafig	match		University Corruption Activist	66359
34	Sahar Al-Khashrami	Profsahar	imprisoned	Fawaz al-Ruwaili	University Corruption	7580
35	Raif Badawi	raif_badawi	imprisoned	Wadad Khaled	Liberal	77643
36	Suliman al-Rashoodi	s_alrushodi	imprisoned	Waleed Sulais	Liberal	35985
37	Saleh al-Ashwan	saleh_alashwan	imprisoned	Taha al-Hajji	Liberal	2943
38	Samar Badawi	samarbadawi15	imprisoned	Hala al-Dosari	Women’s Rights	5134
39	Bandar al-Nogaithan	SaudiLawyer	imprisoned	Sadeq al-Jibran	Judicial Reform	37174
40	Nimr al-Nimr	ShaikhNemer	imprisoned	Saeed Abbas	Shia Cleric	15431
41	Tawfiq al-Amer	sk_tawfeeq	imprisoned	Saeed Abbas	Shia Cleric	550
42	Souad al-Shammari	SouadALshammary	imprisoned	Wadad Khaled	Women’s Rights	246932
43	Taha al-Hajji	tahaalhajji	match	Liberal	7663	16697
44	Turki al-Hamad	TurkiHAlhamad1	imprisoned	Mohamad Ali Mohamed	Liberal	283607
45	Waleed Abul Khair	WaleedAbulkhair	imprisoned	Waleed Sulais	Liberal	89906
46	Waleed Sulais	WaleedSulais	match		Liberal	21297
47	Rashad Hassan	watheh1	match		Professor	249871
48	Wadad Khaled	wdadkhaled	match		Liberal	56921
49	Yousef Ahmed Qasem	Yqasem	match		Sahwa Cleric	117982
50	Zuhair Kutbi	zuhairkutbi	imprisoned	Waleed Sulais	Liberal	9530

B Interrupted Time Series Analysis, Placebo Tests, and Event Count Models

Using Interrupted Time Series Analysis (ITSA), we first model changes in the volume of online behavior as follows:

$$Y_t = \beta_0 + \beta_1(T) + \beta_2(X_t) + \beta_3(X_t T) \quad (1)$$

In Equation 1, Y_t is the number of tweets (or google searches) made at time t, T is the time (number of days) since the opinion leader was imprisoned, X_t is a dummy variable representing political imprisonment (for imprisoned opinion leaders the pre-arrest period is coded as 0 and the post-release period is coded as 1[1]), and $X_t T$ is an interaction term. β_0 represents the baseline volume of tweets (or Google searches) produced at $t = 0$, β_1 shows the change in the volume of tweets (or google searches) associated with a one unit time increase, representing the underlying daily pre-arrest trend. β_2 captures the immediate effect of the arrest on the volume of tweets (or google searches) produced, or an intercept change, and β_3 captures the slope change in the volume of tweets (or google searches) following the release, relative to the pre-arrest trend. In other words, ITSA is a segmented regression model. Segmented regression simply refers to a model with different intercept and slope coefficients for the pre and post-intervention time periods. It is used to measure the pre-arrest trend, the immediate change in the volume of tweets (or google searches) following the release, as well as the change in the slope of the daily volume of tweets (or google searcehs) in the post-release period. In order to address serial autocorrelation in our data, we use a first order autoregressive (AR1) model in our analysis instead of the standard OLS ITSA model (Bernal 2016). If repression is followed by increased online activity, then we should see a positive shift immediately after the release β_2 or a non-negative immediate effect β_2 followed by a positive slope change in the volume of tweets in the post-release period β_3. If repression acts as a deterrent, then we should see a a negative shift immediately after the release β_2 or a non-positive immediate effect β_2 followed by a negative slope change in the volume of tweets in the post-release period β_3. The results of this interrupted time series analysis are reported in subsection B.1 below.

While the advantage of this model is that it enables us to capture both the immediate effect of political imprisonment as well as the longer term effects, it is a linear model and may not be well suited to our count data. To address this concern, we first conduct placebo tests that offer a non-parametric test of our hypotheses. In particular we estimate the effect of the arrests by choosing "intervention dates" at random over the 30 days preceding and 30 days following the actual arrests in our month analyses and the 365 days preceding and following the arrests in our year analyses. We repeated this procedure 10,000 times for each analysis to generate a null distribution of the parameter estimate. We then computed a p-value by calculating the proportion of simulated coefficient estimates that are at least the size of the actual observed estimate. These results are reported in the main body of the paper.

Finally, given that our outcome variable is count data, we also replicate our analyses using event count models—specifically Negative Binomial Autoregressive models—to as-

[1] If opinion leaders were not released from prison in the period under study they are excluded from the analysis. The release dates, as well as those opinion leaders that were not released, are described in Table A2 in the Appendix.

sess the effect of arrests on the volume of tweets produced by imprisoned opinion leaders, mentions and retweets of imprisoned opinion leaders, tweets produced by non-imprisoned opinion leaders, and the Google Trends data. These results are also consistent with the results of our interrupted time series analysis and are displayed in Table A12.

B.1 Interrupted Time Series Analyses

Table A4: Effect of Political Imprisonment on Daily Volume of Tweets
(Imprisoned Opinion Leaders)
One Month Pre-Arrest vs. One Month Post-Release

	Model 1
Baseline	274.696^{***}
	(32.129)
Pre-Arrest Trend	-0.651
	(1.798)
Post-Release Level Change	-190.549^{***}
	(41.344)
Post-Release Slope Change	0.814
	(2.693)
AIC	626.965
BIC	639.117
Log Likelihood	-307.483
Num. obs.	60

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A5: Effect of Imprisonment on Daily Volume of Tweets
(Imprisoned Opinion Leaders)
One Year Pre-Arrest vs. One Year Post-Release

	Model 1
Baseline	301.557^{***}
	(12.440)
Pre-Arrest Trend	-0.013
	(0.059)
Post-Release Level Change	-165.497^{***}
	(17.498)
Post-Release Slope Change	-0.100
	(0.084)
AIC	8355.648
BIC	8383.174
Log Likelihood	-4171.824
Num. obs.	730

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Figure A1: Effect of Imprisonment on Daily Volume of Tweets
(Imprisoned Opinion Leaders)

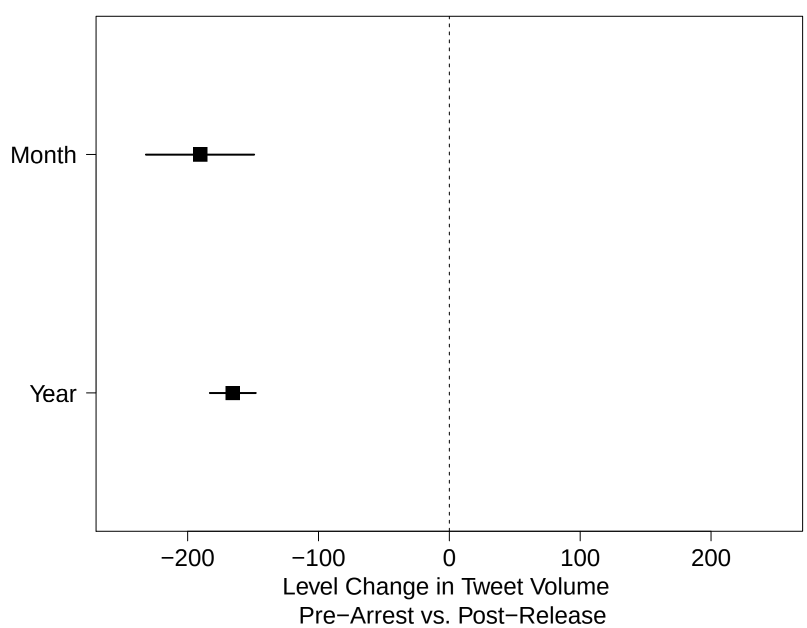


Table A6: Effect of Imprisonments on Daily Volume of Mentions, Replies, and Retweets
One Month Pre-Arrest vs. One Month Post-Arrest

	Model 1
Baseline	36865.670^{***}
	(7590.993)
Pre-Arrest Trend	633.552
	(425.249)
Post-Arrest Level Change	4475.659
	(9838.871)
Post-Arrest Slope Change	-1687.593^{**}
	(610.016)
AIC	1276.251
BIC	1288.509
Log Likelihood	-632.126
Num. obs.	61

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A7: Effect of Imprisonments on Daily Volume of Mentions, Replies, and Retweets
One Year Pre-Arrest vs. One Year Post-Arrest

	Model 1
Baseline	18905.851^{***}
	(1412.542)
Pre-Arrest Trend	6.178
	(6.687)
Post-Arrest Level Change	-1850.453
	(1978.944)
Post-Arrest Slope Change	7.742
	(9.485)
AIC	15160.490
BIC	15188.024
Log Likelihood	-7574.245
Num. obs.	731

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Figure A2: Effect of Imprisonment on Daily Volume of Mentions, Retweets, and Replies
(Engaged Followers)

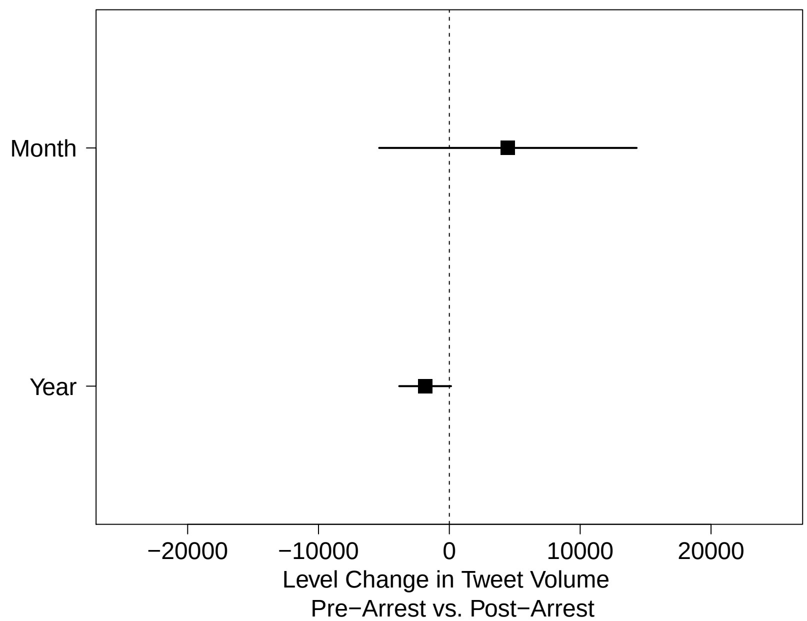


Table A8: Effect of Political Imprisonments on Daily Search Volume
One Month Pre-Arrest vs. One Month Post-Arrest

	Model 1
Baseline	473.727
	(11407.545)
Pre-Arrest Trend	13.828
	(12.752)
Post-Arrest Level Change	319.172^{***}
	(69.856)
Post-Arrest Slope Change	-36.628^{*}
	(17.886)
AIC	662.689
BIC	674.947
Log Likelihood	-325.344
Num. obs.	61

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A9: Effect of Political Imprisonments on Weekly Search Volume
One Year Pre-Arrest vs. One Year Post-Arrest

	Model 1
Baseline	54.476^{***}
	(5.291)
Pre-Arrest Trend	0.113^{***}
	(0.025)
Post-Arrest Level Change	-0.020
	(7.433)
Post-Arrest Slope Change	-0.224^{***}
	(0.035)
AIC	5214.140
BIC	5239.754
Log Likelihood	-2601.070
Num. obs.	532

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Figure A3: Effect of Imprisonment on Daily Volume of Mentions, Retweets, and Replies
(Engaged Followers)

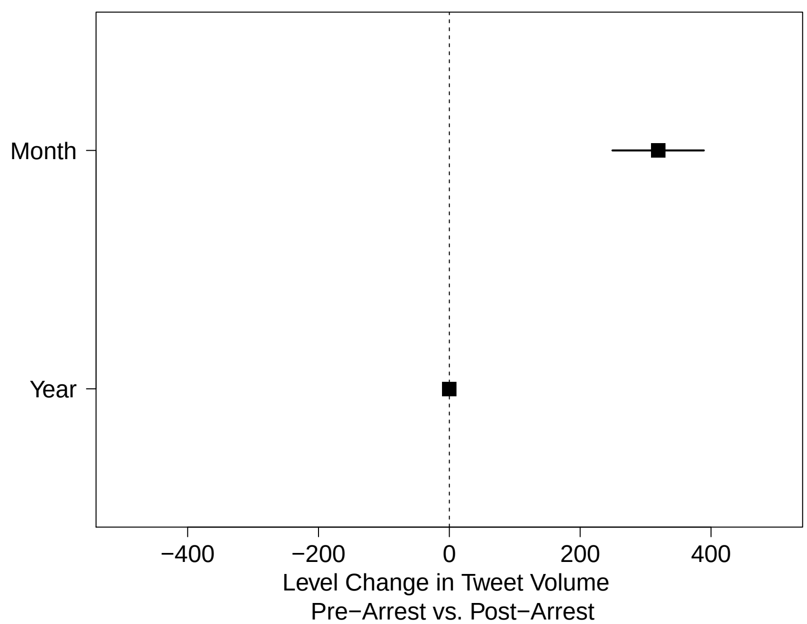


Table A10: Effect of Political Imprisonments on Daily Volume of Tweets
(Non-Imprisoned Opinion Leaders)
One Month Pre-Arrest vs. One Month Post-Arrest

	Model 1
Baseline	339.406^{***}
	(35.448)
Pre-Arrest Trend	1.598
	(1.986)
Post-Arrest Level Change	36.118
	(46.206)
Post-Arrest Slope Change	-3.565
	(2.839)
AIC	667.534
BIC	679.792
Log Likelihood	-327.767
Num. obs.	61

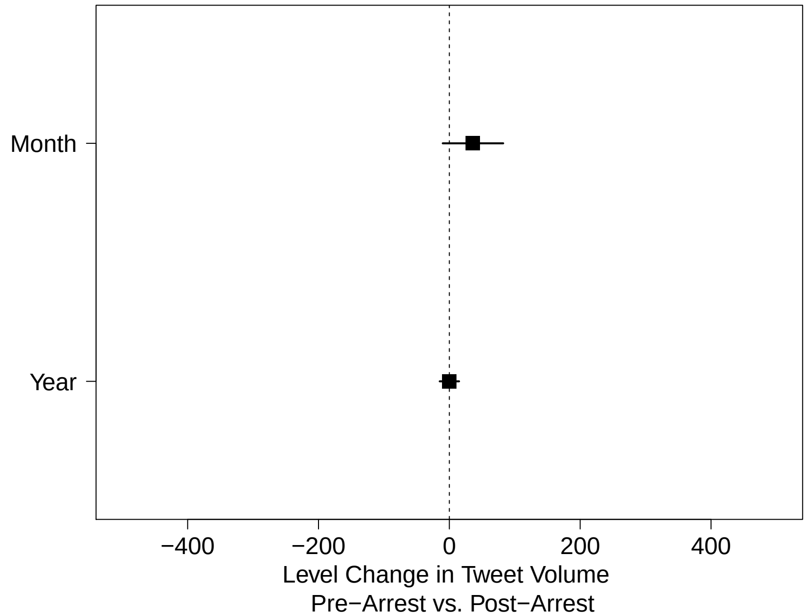
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A11: Effect of Political Imprisonments on Daily Volume of Tweets
(Non-Imprisoned Opinion Leaders)
One Year Pre-Arrest vs. One Year Post-Arrest

	Model 1
Baseline	312.225^{***}
	(10.560)
Pre-Arrest Trend	0.070
	(0.050)
Post-Arrest Level Change	0.071
	(14.813)
Post-Arrest Slope Change	-0.274^{***}
	(0.071)
AIC	8128.078
BIC	8155.612
Log Likelihood	-4058.039
Num. obs.	731

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Figure A4: Effect of Imprisonment on Daily Volume of Tweets
(Non-Imprisoned Opinion Leaders)



B.2 Event Count Models

Table A12: Effect of Poltical Imprisonment on Tweets, Mentions, and Search Volume
Negative Binomial Event Count Models

	Arrested Month	Arrested Year	Match Month	Match Year	Mentions Month	Mentions Year	Google Trends Month	Google Trends Year
Post-Arrest/Release	-1.19***	-0.97***	0.08	-0.09***	-0.14	0.08***	0.61**	-0.003
	(0.08)	(0.03)	(0.05)	(0.02)	(0.13)	(0.03)	(0.20)	(0.09)
Constant	6.85***	6.69***	5.68***	5.79***	10.39***	9.71***	3.62***	3.52***
	(0.13)	(0.05)	(0.08)	(0.03)	(0.21)	(0.05)	(0.33)	(0.14)
AIC	641.48	8330.97	682.73	8236.51	1327.68	15124.28	711.14	4416.16
Num. obs.	60.00	730.00	61.00	731.00	61.00	731.00	61.00	532.00

This table shows the results of our negative binomial event count models. As in all of our analysis, for the arrested opinion leaders, we compare the pre-arrest period to the post-release period. For the rest of the analyses, we compare the pre-arrest period to the post-arrest period.

B.3 Engaged Followers Excluding Those Who Tweeted Post-Arrest Only

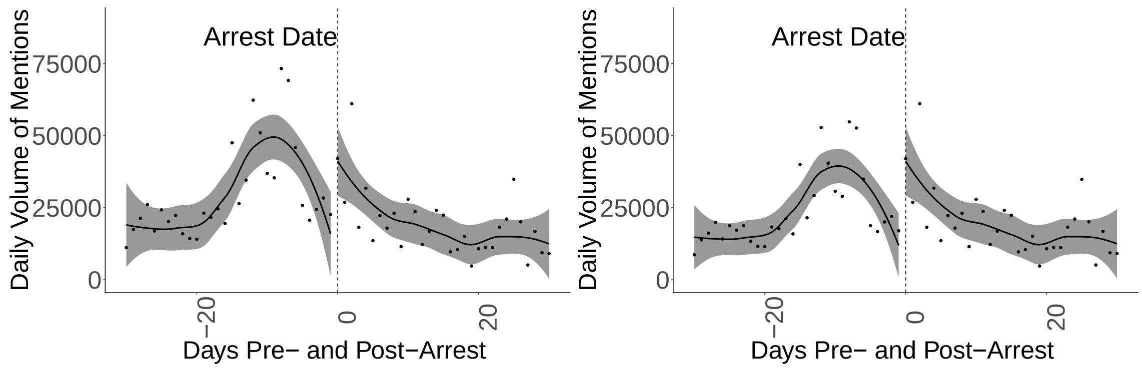


Figure A5: Daily volume of mentions and retweets of imprisoned opinion leaders in the month pre and post-arrest (left panel) and in the year pre and post-arrest (right panel) plotted as local regression lines with loess smoothing. Here the data is subset only to users who engaged with the imprisoned opinion leader at least once in the pre-arrest period.

C Disaggregated Effects

It is possible that the effects we observe are driven by particular opinion leader arrests and that the effects might differ across arrest length, time of the arrest, whether or not the opinion leader was explicitly Imprisoned for online activity, follower count, and opinion leader type (liberal reformers, Sunni clerics, and Shia clerics and activists). To test this we conduct subgroup analyses comparing average pre-arrest and post-arrest (or release) tweet volume and google search volume for the imprisoned opinion leaders themselves, similar non-imprisoned opinion leaders, those who retweet or mention the opinion leaders, and google search volume for the imprisoned opinion leaders names. Overall we see no significant differences across these subgrups. These results are reported in Figures A6-A9.

We disaggregate individuals into three groups: liberal reformers, Sunni clerics, and Shia reformers. Liberal reforms include human rights activists, legal activist, and women's rights activists. We see very little difference (and none of the differences are statistically significant) in non-arrested elite tweets, mentions or retweets of arrested elites, or Google Searches between these three groups (Figures A7-A9). We do see a smaller decrease in tweets by Shia among the imprisoned opinion leaders themselves (Figure A6), but this is a function of the fact that the Shia opinion leaders in our sample tweet less both pre-arrest and post-release than the other actors so the effect (while in the same direction) is smaller.

There are no statistically significant differences in tweets by imprisoned opinon leaders or in mentions or retweets by engaged followers, or in tweets sent by similar non-imprisoned opinion leaders for opinion leaders with low numbers of followers compared to opinion leaders with high numbers of followers (Figures A6-A9).[2] However we do see a statistically significantly higher number of Google searchers for opinion leaders with

[2]Here we compare those with below the median number of followers (21,574) to those with above the median number of followers.

high numbers of followers relative to those with low numbers of followers. Perhaps this is due to the fact that more prominent individuals (who likely have more followers on Twitter) got more press coverage following their arrests. For everyday Saudis who don't necessarily follow these individuals online, arrests of more prominent individuals likely garnered more attention.

When we disaggregate by period, for the imprisoned opinion leaders (Figure A6), the decrease in their volume of tweets is statistically significantly greater in 2010-2012 and 2013-2015 relative to 2016-2017. This is likely because although several opinion leaders were arrested in 2016-2017, the only imprisoned opinion leader who was arrested and released before our data collection period ended in January 2017—allowing us to measure these pre-arrest and post-release differences—was Samar Badawi. She is a women's rights and human rights activist whose brother was also imprisoned in this period, perhaps prompting her to keep tweeting following her release. She was only detained for 3 days in 2016 and may not have been as deterred as the other opinion leaders in part because of her family connections. Looking at changes in the volume of mentions and retweets of imprisoned opinion leaders and tweets by similar non-imprisoned opinion leaders we see no significant differences between the time periods (Figures A7 and A8). With regard to Google searches (Figure A9), it appears that political imprisonment between 2010-2012 garnered slightly more search interest then imprisonment in the other periods—perhaps because these events were of particular interest in the early days of the Arab Spring.

While all of the elites in our study were speculated to have been arrested for their online activity, the official Saudi government rationale for the arrests did not always include online activity. For example, the official reason for the imprisonment of the three judicial reform activists was "disobeying rule / slandering judiciary," but according to media and observer reports, the "disobedience" and "slander" all took place on Twitter (see Table A1 for details for every arrested individual). When we disaggregate based on whether or not they were explicitly imprisoned, we observe no differences (Figures A6-A9) in imprisoned opinion leader tweets, non-imprisoned opinion leader tweets, mentions or retweets of imprisoned opinion leaders, or Google searches. Perhaps this is because all of the individuals were effectively imprisoned for online activity even though this was only made explicit in certain cases.

With regard to arrest length, there are no significant differences across our analyses of different actors (A6-A9. Here we compare those arrested for below the median number of days (70) to those arrested for above the median number of days (70).

Figure A6: Disaggregated Effect of Political Imprisonment on Imprisoned Opinion Leader Tweet Volume

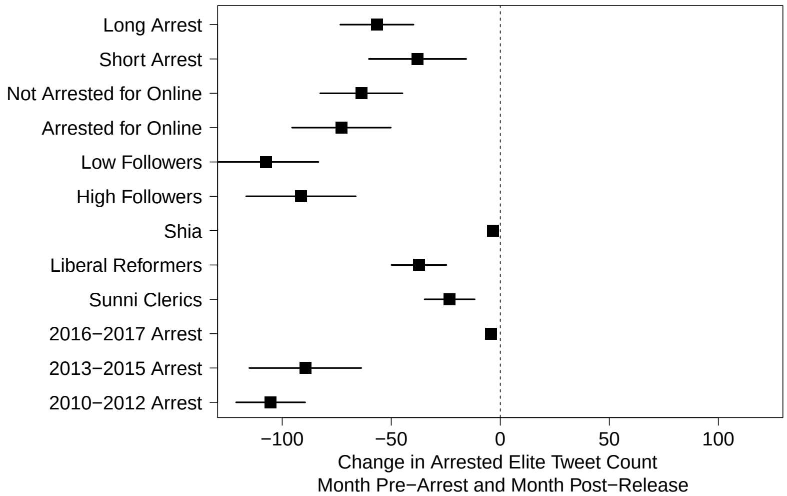


Figure A7: Disaggregated Effect of Political Imprisonment on Non-Imprisoned Opinion Leader Tweet Volume

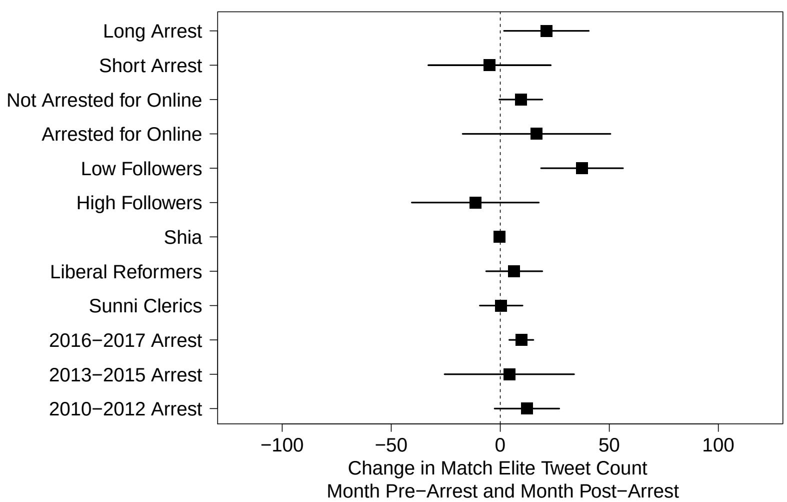


Figure A8: Disaggregated Effect of Political Imprisonment on Volume of Mentions and Retweets of Imprisoned Opinion Leaders

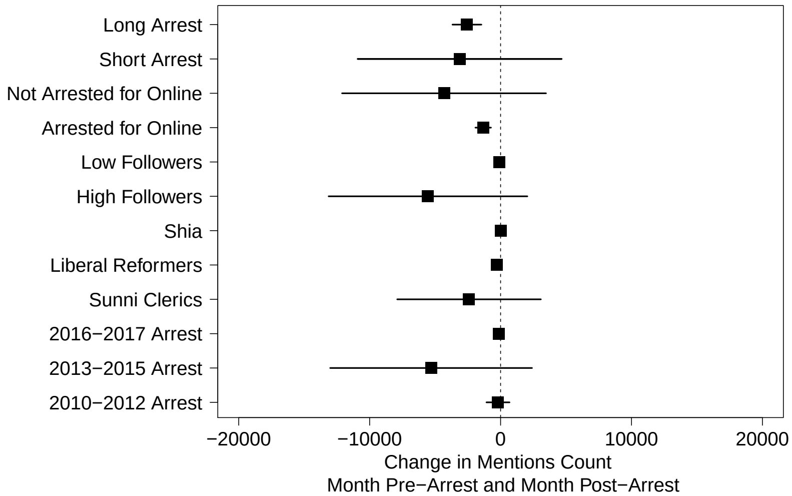
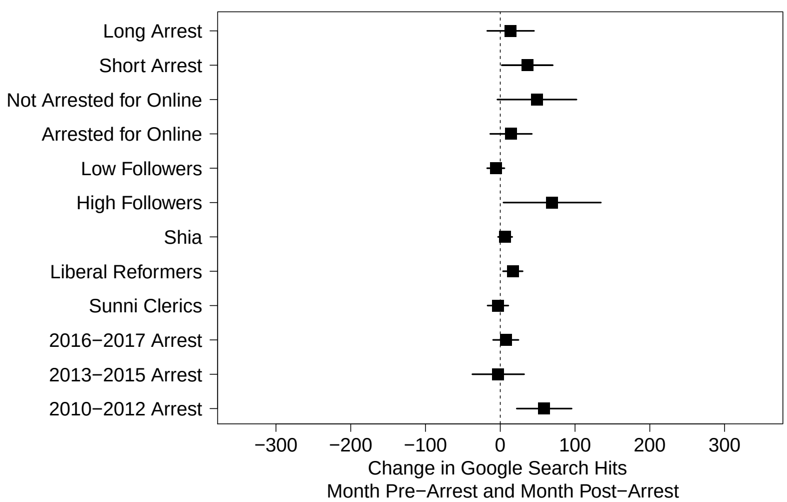


Figure A9: Disaggregated Effect of Political Imprisonment on Google Searches of Imprisoned Opinion Leaders



D Content Analysis

We used Figure8 to code about 10,000 tweets produced by arrested and non-imprisoned opinion leaders and about 20,000 tweets produced by the engaged followers of imprisoned opinion leaders for a total of approximately 30,000 coded tweets. 5,000 of the opinion leader tweets were selected through stratified random sampling of all tweets produced by the arrested and non-imprisoned opinion leaders over the month preceding arrest and the month following release, balanced by actor type (Sunni clerics, women's rights activists, liberal activists, lawyers, anti-corruption activists, and Shia rights activists). The other 5,000 tweets were sampled from all opinion leader tweets produced between six months and one year following arrest, again balanced by actor type. We did not collect data from a year pre-arrest because substantively we wanted to compare content produced in the lead-up to the arrest (the period during which the regime decided to constrain the opinion leaders' behavior) with content produced in the immediate aftermath of repression and in the longer term. We similarly sampled tweets that mentioned or retweeted the imprisoned opinion leaders (another 10,000 tweets), and finally sampled tweets containing political keywords that were produced by the opinion leaders' engaged followers (another 10,000 tweets).

Three native Arabic speakers assessed each tweet on the Figure8 platform. The coding scheme used by the Figure8 workers is presented in detail in subsection D.1. Across all samples, intercoder agreement was very high, with 95% agreement among coders on average. The reason why intercoder reliability appears so high in our data is that the majority of tweets in our large random sample were coded as not relevant to the Saudi regime, polices, society, or collective action and agreement on relevance (which is easier to assess than sentiment) is very high across the questions. Agreement on whether tweets in each category were positive, negative, or neutral was somewhat lower—about 80% on average—though still a reasonable measure. A table of average intercoder agreement by coding category can be found in Table A13. The majority of tweets about the Saudi regime, policies, and society expressed negative sentiment (72%, 75%, and 60% respectively) and very few tweets called for collective action (less than 1% of all coded tweets). Histograms of these proportions can be found in Figure A10.

D.1 Figure8 Coding Scheme

Overview: In this job you will be presented with Arabic language tweets related to society and politics posted by Saudi Arabian Twitter users. You will answer several brief questions about the content of each tweet.

Steps:

- Read each tweet carefully.
- Answer a series of brief questions about the content of each tweet.

1. What attitude does this tweet express about the Saudi monarchy, ruling regime, leaders, religious establishment, or religious doctrine?

- Positive
- Negative
- Neutral
- Irrelevant
- Unclear

2. What attitude does this tweet express about Saudi policies or bureaucracy?

- Positive

- Negative
- Neutral
- Irrelevant
- Unclear

3. What attitude does this tweet express about Saudi society?

- Positive
- Negative
- Neutral
- Irrelevant
- Unclear

4. Is this tweet calling for collective action (social mobilization to achieve a particular goal)?

- Yes
- No
- Unclear

Question 1 Instructions:

- Positive tweets include tweets praising or expressing satisfaction with the Saudi monarchy, ruling regime, leaders, religious establishment, or religious doctrine such as tweets praising specific royal family members or clerics, tweets supporting the legitimacy of the Saudi regime or religious establishment, or tweets praising Saudi Wahabbi religious doctrine.
- Negative tweets include tweets expressing dissatisfaction with or critical of the Saudi monarchy, ruling regime, leaders, religious establishment, or religious doctrine such as tweets criticizing specific royal family members or clerics, tweets calling for democracy or other forms of government, or tweets criticizing Saudi Wahabbi religious doctrine.
- Neutral tweets neither express satisfaction nor dissatisfaction with the Saudi monarchy, ruling regime, leaders, religious establishment, or religious doctrine. These include news articles or factual statements about the regime or religious establishment.
- Irrelevant tweets do not mention the Saudi monarchy, ruling regime, leaders, religious establishment, or religious doctrine.

Question 2 Instructions:

- Positive tweets include tweets praising or expressing satisfaction with the Saudi bureaucracy including the judiciary, the ministry of education, or the religious police. They also include tweets praising or expressing satisfaction with policies and policy outcomes including the state of the economy, corruption, foreign policy, or infrastructure.
- Negative tweets include tweets expressing dissatisfaction with or critical of the Saudi bureaucracy including the judiciary, the ministry of education, or the religious police. They also include tweets criticizing or expressing dissatisfaction with policies and policy outcomes including the state of the economy, corruption, foreign policy, and infrastructure.
- Neutral tweets neither express satisfaction nor dissatisfaction with Saudi policies or bureaucracy. These include news articles or factual statements about policies or bureaucracy.
- Irrelevant tweets do not mention Saudi policies or bureaucracy.

Question 3 Instructions:

- Positive tweets include tweets expressing satisfaction with or praising Saudi society including the role of women, the piety or industriousness of the population, or youth culture.
- Negative tweets include tweets expressing dissatisfaction with or critical of Saudi society, including tweets criticizing Saudi society for being too liberal or conservative or tweets criticizing the role of women in society or youth culture.
- Neutral tweets neither express satisfaction nor dissatisfaction with Saudi society. These include news articles or factual statements about Saudi society.
- Irrelevant tweets do not mention Saudi society.

Question 4 Instructions:

- Tweets calling for collective action (social mobilization to achieve a specific goal) include tweets discussing protest or organized crowd formation.

D.2 Intercoder Agreement

Table A13: Average Intercoder Agreement

	n	mean	sd
policies	16764	0.93	0.15
regime	16764	0.93	0.15
society	16764	0.95	0.13
collective action	16764	0.99	0.05

This table shows average intercoder agreement by category among the three human coders that coded each tweet on Figure8.

Figure A10: Distribution of Tweet Content

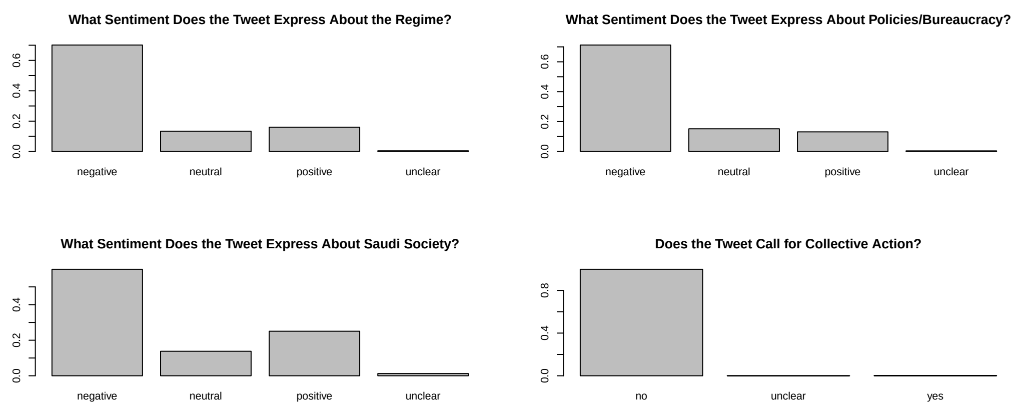
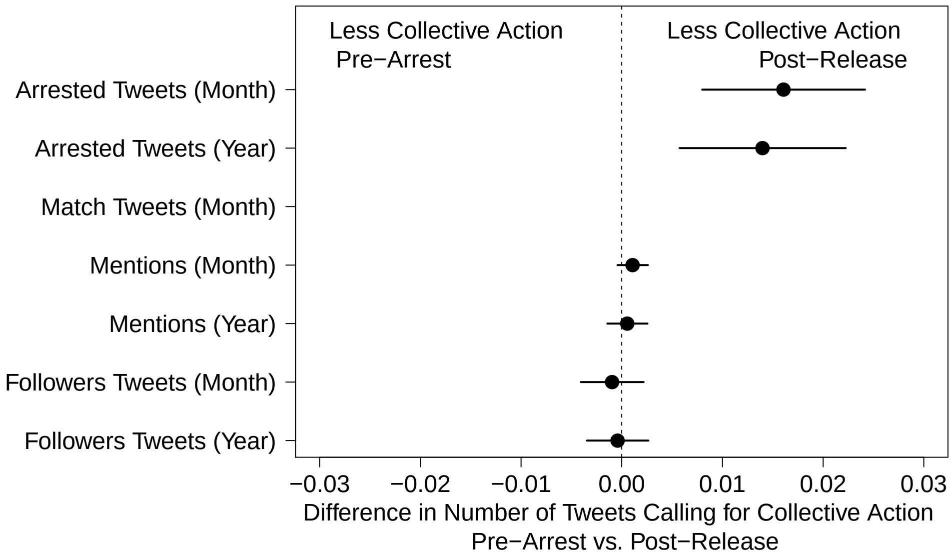


Figure A11: Top Political Keywords in opinion leader Tweets Relevant to Regime, Policies, or Society

keyword	**translation**	**keyword**	**translation**	**keyword**	**translation**
سلمان	King Salman	السجناء	prisoners	السيدات	women
الداخلية	Interior Ministry	منظمة	organization	تخاف	fear
الملك	King	المواطن	citizens	الشيعة	the Shia
نايف	Nayef (Interior Minister)	سياسي	political	سياسيا	politics
الناس	the people	خلف	behind/backwards	موافقة	agreement
السلطة	power	#داعش	#Daesh (ISIS)	النمر	Al-Nimr (Shia cleric)
النساء	women	المواطنين	citizens	الامير	prince
السياسية	politics	الأمير	prince	الشيعي	Shia
النظام	regime	الحاكم	rule	القطاع	sector
التعليم	education	القضاء	judge	حقوق	rights
وزارة	ministry	الحقوق	rights	الطائفية	sectarianism
المرأة	women	هوية	identity	الشرطة	police
الحكم	governance	القرار	decision	الحق	rights
وزير	minister	سياسة	politics	الجيش	army
ولي	crown	oct26driving	oct26driving	الحر	free
الدولة	the state	هدر	waste	إسرائيل	Israel
الشعب	the people	الخاص	private	السياسة	politics
الحكومة	government	القانون	law	الحوثيين	Houthi
women	women	موقع	position	الحرب	war
#مصر	egypt	حرب	war	واضح	clear
العلمية	academic research	مشروع	project	جامعة	university
العدل	justice	مصر	egypt	السرقات	theft
المجتمع	society	الجمعة	university	الجامعات	universities
سجن	prison	السياسي	political	قتل	killed
الفساد	corruption	اهل	people	اليمن	Yemen
قيادة	leadership	الظلم	injustice		
سوريا	Syria	وكيل	representative		
المصري	Egyptian	معالي	his excellency		
الوطن	homeland	#هلكوني	#they_stole_from_me		
ملف	issue	العمل	work		
#سرقوني	#they_stole_from_me	القطيف	Qatif (Shia region)		

E Collective Action Results

Figure A12: Change in Average Number of Tweets Calling for Collective Action



This figure shows the results of t-tests evaluating the change in the average number of tweets calling for collective action in tweets produced by imprisoned opinion leaders, tweets produced by similar non-imprisoned opinion leaders, tweets mentioning or retweeting imprisoned opinion leaders, and tweets sent by the engaged followers of imprisoned opinion leaders one month before the arrests and one month and one year following the releases. Each tweet was coded by three coders on Figure8 as either containing discussions of collective action or not.

Figure A13: Change in Proportion of Tweets Calling for Collective Action