Supplementary Appendix:

How Exile Shapes Online Opposition:
Evidence from Venezuela

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# Contents

Appendix A: Additional Information

A.1 Expert Dictionary Validation

In order to ensure that our word2vec dictionary approach accurately classified tweets, we had a Spanish speaker with expertise in Venezuelan politics code a stratified random sample of 2000 tweets (500 classified in each topic) according to whether each tweet was correctly classified as relevant to criticism of the regime, foreign action, protest, or service provision. As Figure A1 below suggests, between 93 and 97% of tweets were coded by our expert coder as relevant across all four topics. Between 1 and 3% of tweets were coded as irrelevant, and between 3 and 4% of tweets were unclear across all four topics.

Figure A1: Expert Validation of Word2Vec Dictionary Classification
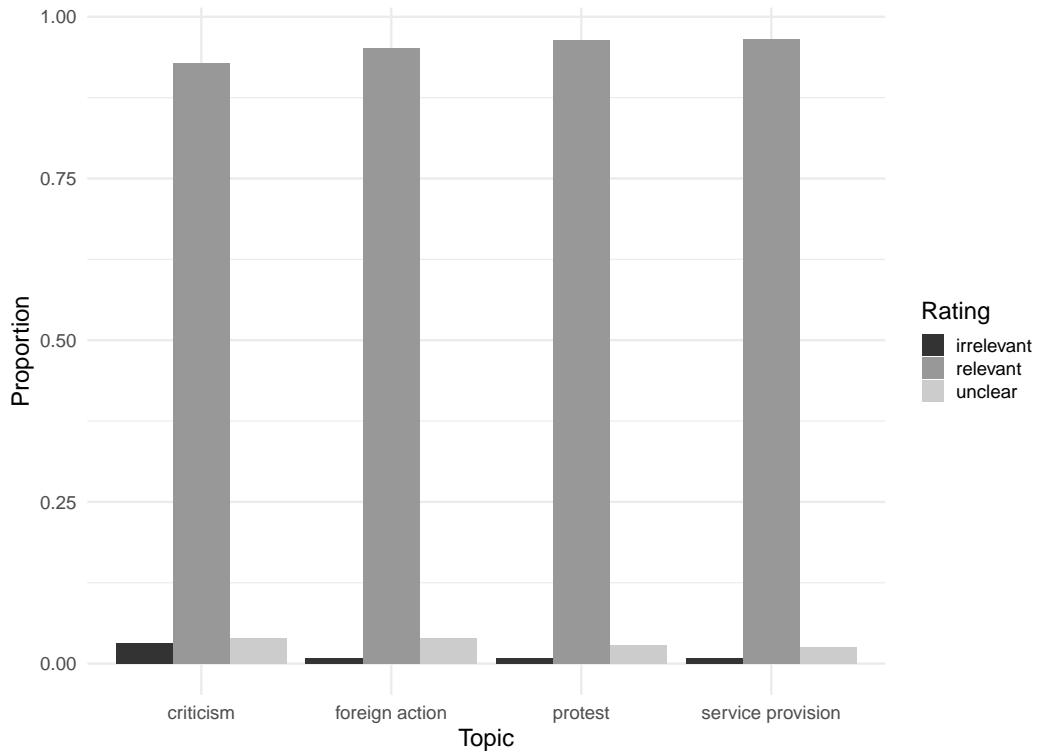
A.2   Topics Over Time (Raw Data)

Figure A2: Weekly Volume of Tweets Referencing Primary Topics
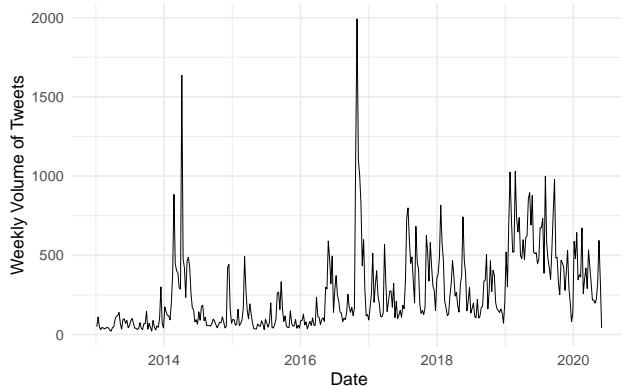
Foreign Policy
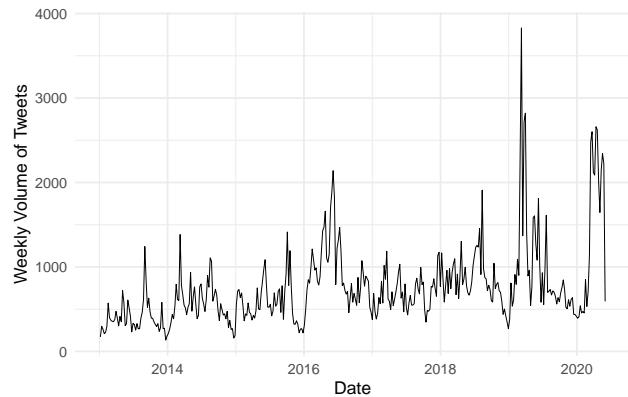
Service Provision
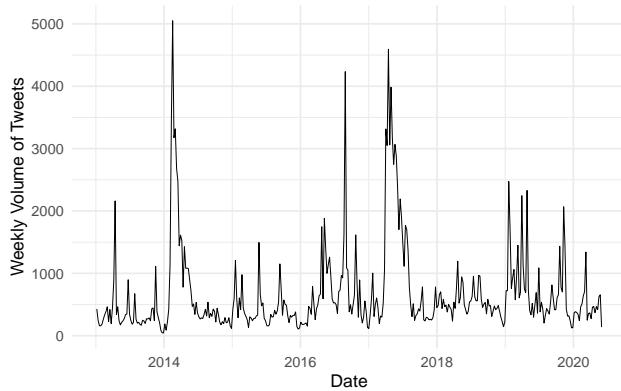
Protest
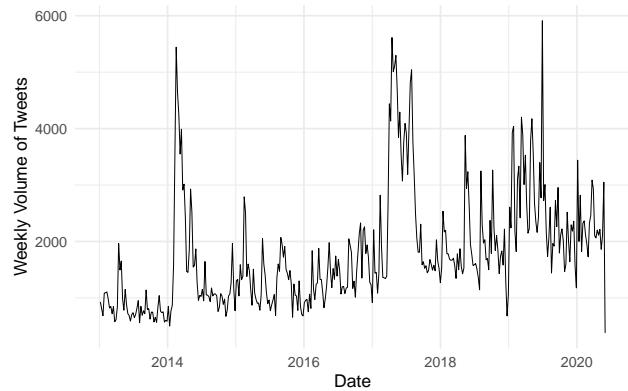
Harsh Criticism

Figure A3: Mean Weekly Volume of Tweets Referencing Primary Topics
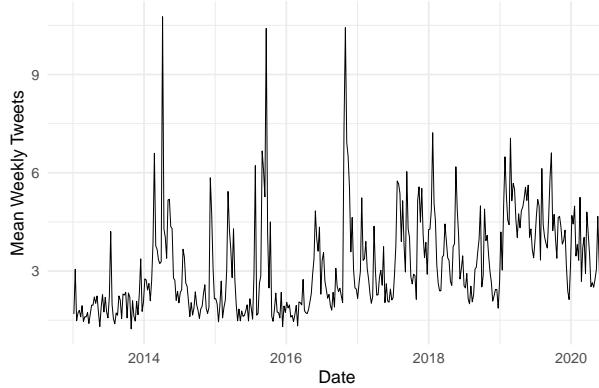
Foreign Policy
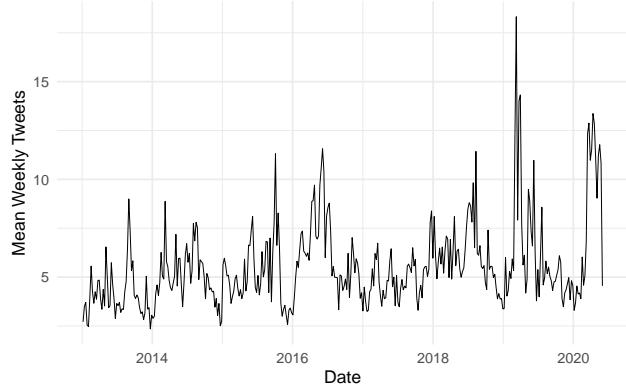
Service Provision
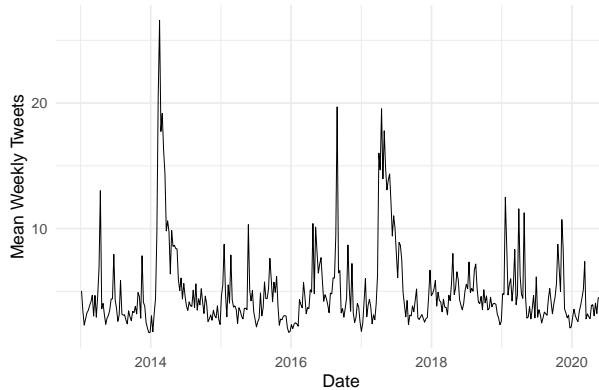
Protest
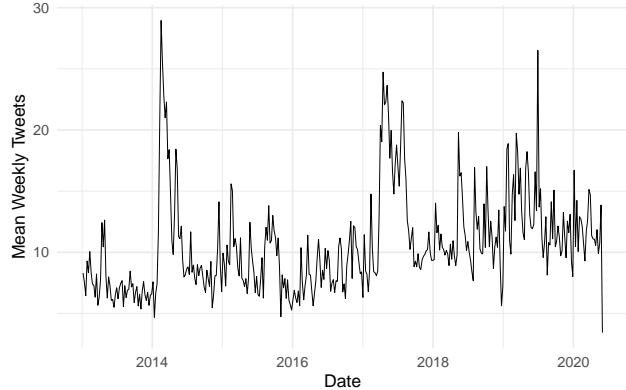
Harsh Criticism

Figure A4: Mean Weekly Proportion of Tweets Referencing Primary Topics
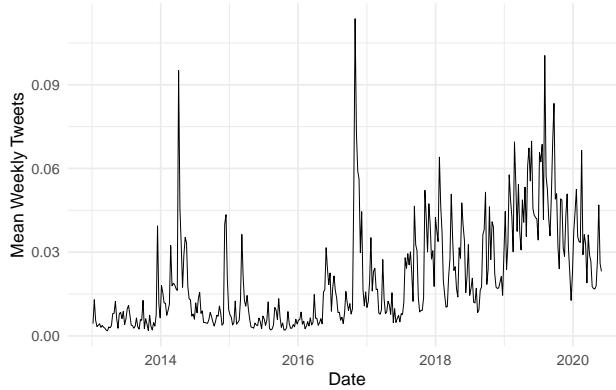
Foreign Policy

Service Provision
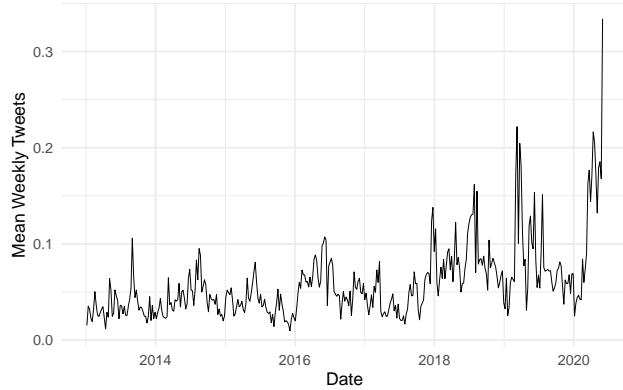
Protest
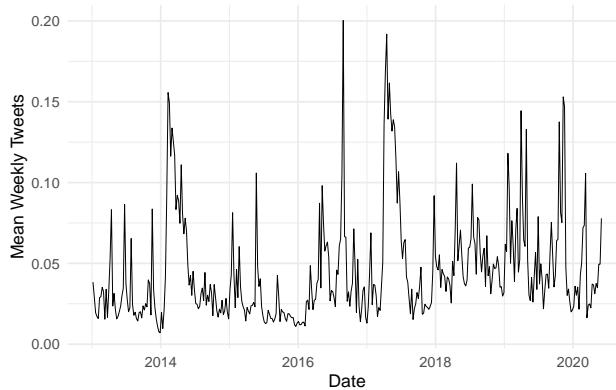
Harsh Criticism
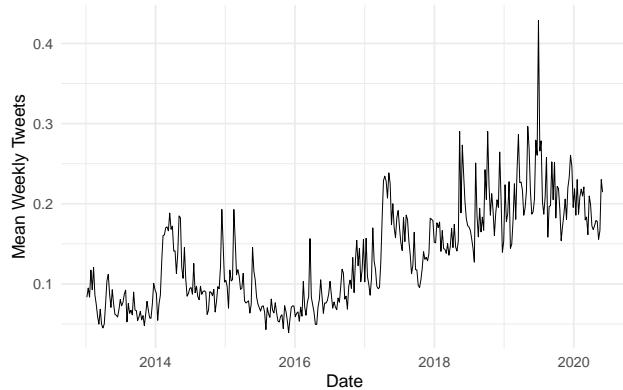
A.3   Supporting Tables

Table A1: Foreign Policy Terms and Exile

|	Overall Foreign Policy			Military Intervention		
Tweeted from Exile	2.742***	2.117***	1.505***	0.318***	0.249***	0.203**
	(0.619)	(0.491)	(0.431)	(0.117)	(0.085)	(0.089)
Number of Tweets	0.109**	0.120***	0.090*	0.012	0.007	0.007
	(0.049)	(0.043)	(0.046)	(0.007)	(0.009)	(0.007)
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.161	0.154	0.265	0.059	0.059	0.213

	Economic Sanctions			Diplomacy		
Tweeted from Exile	1.276**	1.086**	0.721**	1.249***	0.858***	0.673***
	(0.589)	(0.429)	(0.296)	(0.195)	(0.196)	(0.251)
Number of Tweets	0.032	0.044**	0.041*	0.069*	0.074**	0.045
	(0.030)	(0.020)	(0.024)	(0.037)	(0.034)	(0.039)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.086	0.083	0.320	0.134	0.125	0.183

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A2: Service Provision Terms and Exile

	Service Provision		
Tweeted from Exile	−2.841***	−3.727***	−1.281***
	(0.415)	(0.430)	(0.495)
Number of Tweets	0.358***	0.286***	0.354***
	(0.085)	(0.093)	(0.081)
Month/Year FE	Y	Y	Y
User FE	Y	N	Y
User trend	N	N	Y
Observations	22,669	22,669	22,669
R^2	0.198	0.190	0.266

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A3: Protest Terms and Exile

	Protest		
Tweeted from Exile	−0.746***	−1.178***	−0.618*
	(0.287)	(0.308)	(0.331)
Number of Tweets	0.289***	0.269***	0.375***
	(0.070)	(0.068)	(0.077)
Month/Year FE	Y	Y	Y
User FE	Y	N	Y
User trend	N	N	Y
Observations	22,669	22,669	22,669
R^2	0.203	0.187	0.254

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A4: Harsh Criticism and Exile

	Harsh Criticism			Narco-State		
Tweeted from Exile	6.374***	7.520***	3.502**	2.005***	1.631***	1.457***
	(1.276)	(1.626)	(1.529)	(0.471)	(0.493)	(0.417)
Number of Tweets	0.053	0.619***	0.167	0.089	0.137**	0.110*
	(0.173)	(0.209)	(0.162)	(0.057)	(0.056)	(0.056)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.233	0.204	0.345	0.149	0.142	0.243

	Dictator			Cuban/Russian Influence		
Tweeted from Exile	4.361***	3.641***	2.498***	0.616**	1.005***	0.201
	(0.780)	(0.877)	(0.734)	(0.255)	(0.247)	(0.301)
Number of Tweets	0.200**	0.268**	0.315***	−0.005	0.123**	0.023
	(0.097)	(0.107)	(0.093)	(0.059)	(0.051)	(0.057)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.251	0.232	0.365	0.037	0.041	0.110

	Repression		
Tweeted from Exile	2.862***	4.084***	0.904
	(0.949)	(1.127)	(1.478)
Number of Tweets	−0.052	0.331**	−0.034
	(0.121)	(0.157)	(0.130)
Month/Year FE	Y	Y	Y
User FE	Y	N	Y
User trend	N	N	Y
Observations	22,669	22,669	22,669
R^2	0.155	0.124	0.248

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A5: Foreign Content and Exile

	Foreign Actors			US Terms		
Tweeted from Exile	7.425***	8.232***	4.992***	2.175***	3.397***	1.005***
	(0.711)	(0.928)	(0.751)	(0.444)	(0.648)	(0.329)
Number of Tweets	0.341*	0.679***	0.229	0.094	0.217***	0.049
	(0.182)	(0.201)	(0.143)	(0.059)	(0.050)	(0.055)
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.216	0.222	0.291	0.108	0.135	0.218
	Foreign Engagement			English		
Tweeted from Exile	10.229***	24.929***	7.017***	1.429***	3.057***	0.882**
	(1.860)	(2.845)	(2.043)	(0.348)	(1.155)	(0.353)
Number of Tweets	−0.375	0.944*	−0.370	−0.239**	−0.028	−0.178***
	(0.369)	(0.543)	(0.326)	(0.100)	(0.102)	(0.053)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	19,020	19,020	19,020	22,669	22,669	22,669
R^2	0.071	0.136	0.148	0.017	0.026	0.242

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A6: Country Mentions by Destination

Tweeted from Exile	0.962***	1.483***
	(0.296)	(0.363)
Number of Tweets	0.082	0.090
	(0.060)	(0.143)
Tweeted from Exile * US Destination	3.604***	
	(1.078)	
Tweeted from Exile * Colombia Destination		3.361***
		(0.871)
Month/Year FE	Y	Y
User FE	Y	N
User trend	N	N

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A7: Event Study Model Results

	Foreign Policy	Service Provision	Protest	Criticism	Foreign Interaction
pre	-0.838^{**}	-0.247	-0.175	-4.341^{***}	-2.240
	(0.382)	(0.731)	(0.521)	(1.528)	(1.533)
-6	-0.240	0.294	-0.152	0.045	-1.524
	(0.489)	(1.110)	(0.686)	(1.842)	(1.597)
-5	-0.171	-0.648	-0.302	-1.610	-0.802
	(0.450)	(0.925)	(0.625)	(2.115)	(1.676)
-4	0.074	0.508	-0.472	-1.998	-1.470
	(0.541)	(0.953)	(0.726)	(1.560)	(1.668)
-3	0.024	-0.588	0.127	-1.002	-1.788
	(0.506)	(0.838)	(1.493)	(1.739)	(1.554)
-2	-0.357	-0.551	0.511	-0.272	-1.867
	(0.424)	(0.761)	(0.682)	(1.185)	(1.717)
0	0.143	-1.538^{**}	-1.156^{**}	1.509	0.749
	(0.431)	(0.737)	(0.587)	(1.812)	(1.663)
1	1.193^{**}	-2.106^{**}	-0.341	4.449^{*}	4.866^{***}
	(0.571)	(0.983)	(0.611)	(2.278)	(1.829)
2	1.797^{***}	-1.390	-0.350	1.537	3.890^{*}
	(0.566)	(0.928)	(0.612)	(1.989)	(2.045)
3	0.956^{*}	-1.572^{*}	0.320	5.737^{***}	6.696^{***}
	(0.492)	(0.922)	(0.770)	(2.108)	(2.199)
4	1.555^{**}	-2.092^{**}	0.074	3.762^{**}	6.358^{***}
	(0.669)	(0.838)	(0.812)	(1.851)	(2.048)
5	2.037^{***}	-2.780^{***}	-0.875	2.371	3.396^{**}
	(0.661)	(0.760)	(0.663)	(2.041)	(1.657)
6	1.719^{***}	-2.270^{**}	0.253	3.503^{*}	4.204^{**}
	(0.624)	(0.925)	(0.760)	(1.972)	(1.668)
7	1.319^{**}	-2.672^{***}	-0.843	6.002^{**}	5.708^{**}
	(0.632)	(1.013)	(0.769)	(2.516)	(2.225)
8	1.921^{**}	-1.656^{*}	-1.479^{**}	2.906	5.985^{***}
	(0.754)	(0.969)	(0.659)	(2.080)	(1.956)
9	1.800^{***}	-3.903^{***}	-0.087	3.931^{*}	6.006^{***}
	(0.627)	(0.918)	(0.759)	(2.138)	(1.973)
10	2.528^{**}	-2.168^{*}	-0.442	5.088^{*}	2.685
	(1.018)	(1.137)	(0.766)	(2.607)	(1.991)
11	1.519^{**}	-2.884^{***}	-1.507^{**}	6.768^{**}	3.600^{*}
	(0.703)	(1.017)	(0.704)	(2.946)	(2.004)
12	2.830^{***}	-3.935^{***}	-1.247^{**}	1.503	6.599^{***}
	(0.902)	(0.752)	(0.605)	(1.901)	(1.697)
Number of Tweets	0.109^{**}	0.364^{***}	0.291^{***}	0.061	0.338^{*}
	(0.048)	(0.085)	(0.070)	(0.172)	(0.182)
Month/Year FE	Y	Y	Y	Y	Y
User FE	Y	Y	Y	Y	Y
Observations	22,609	22,609	22,609	22,609	22,609
R^2	0.164	0.199	0.204	0.236	0.218

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Robust standard errors clustered at the user level.

A.4 Crowd-sourced Human Coding

To create training data to classify tweets according to the position they expressed on economic sanctions or foreign intervention in Venezuela, we used Appen (formerly Figure8 / Crowdflower) a microtask platform to hire three native Spanish speakers to code each tweet. We coded 4000 tweets in total, 2000 with word2vec keywords indicating they referenced military intervention and 2000 with word2vec keywords indicating that they referenced economic sanctions. Intercoder reliability was high—89% across all three coders on average. The English language instructions for the coders were as follows:

Overview: In this job, you will be presented with tweets on the topic of (economic sanctions/foreign intervention) in Venezuela. Review the tweets to determine the relevance to the subject and then answer a series of questions about each tweet.
Classification instructions:

- Read the tweet.

- Determine if the tweet is relevant to the topic.

- If the tweet is relevant, answer the questions about the content of the tweet.

Question 1: Is this tweet related to (economic sanctions/foreign intervention)?

- Yes

- No

- Unclear

If yes:

Question 2: Does this tweet present (sanctions/foreign intervention) as a positive or negative policy option?

- Positive

- Negative

- Neutral

- Unclear

Positive: (Sanctions) Tweets that support the use or discussion of economic sanctions. (Intervention) Tweets that support the use or discussion of foreign intervention, including military intervention, humanitarian intervention, or naval blockades.

Negative: Tweets that denounce or criticize the policies or impacts of (sanctions/foreign intervention).

9

Neutral: Tweets that describe (sanctions/foreign intervention) neither positively nor negatively, like news articles or announcements that do not take a stand about whether or not to use sanctions.

We then used this human coded data to first train two binary Naive Bayes classifiers to remove irrelevant tweets (relevant to military intervention vs. irrelevant and relevant to sanctions vs. irrelevant). We then trained four binary Naive Bayes classifiers on the relevant tweets (pro-military intervention or not, anti-military intervention or not, pro-sanctions or not, and anti-sanctions or not). The classifiers all had high levels of precision and balanced accuracy, ranging from 82-95% across classifiers.

A.5 Classified Military and Sanctions Tweets

Figures A5 and A6 show the results for military intervention and economic sanctions for tweets classified as being relevant to those topics and mentioning them positively or negatively. Results demonstrate that our findings are driven largely by increased positive mentions, with little to no effect on negative references.

Figure A5: Military Intervention   Figure A6: Sanctions
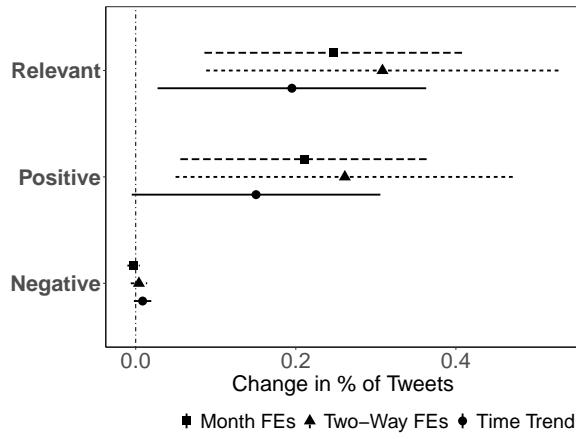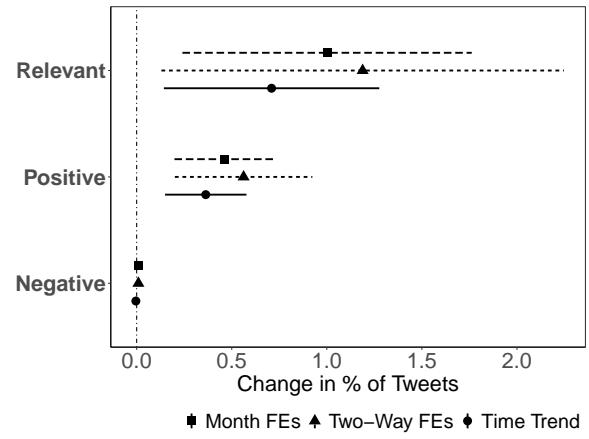
Tabular results for Figures A5 and A6 results can be found in Tables A8 and A9.

Table A8: Classified Intervention Tweets and Exile

	Relevant			Positive		
Tweeted from Exile	0.308***	0.247***	0.195**	0.261**	0.211***	0.150*
	(0.112)	(0.082)	(0.086)	(0.108)	(0.079)	(0.079)
Number of Tweets	0.009	0.004	0.006	0.002	−0.002	−0.002
	(0.007)	(0.009)	(0.006)	(0.006)	(0.009)	(0.006)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.051	0.051	0.206	0.037	0.037	0.213

	Negative		
Tweeted from Exile	0.004	−0.003	0.009
	(0.005)	(0.004)	(0.006)
Number of Tweets	0.004***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)
Month/Year FE	Y	Y	Y
User FE	Y	N	Y
User trend	N	N	Y
Observations	22,669	22,669	22,669
R^2	0.013	0.014	0.035

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

Table A9: Classified Sanctions and Exile

	Relevant			Positive		
Tweeted from Exile	1.188**	1.002***	0.709**	0.562***	0.464***	0.363***
	(0.540)	(0.388)	(0.289)	(0.184)	(0.135)	(0.109)
Number of Tweets	0.024	0.041**	0.034	0.006	0.009	0.007
	(0.027)	(0.018)	(0.022)	(0.010)	(0.008)	(0.010)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.084	0.083	0.297	0.067	0.070	0.161

	Negative		
Tweeted from Exile	0.009	0.009	−0.004
	(0.008)	(0.006)	(0.009)
Number of Tweets	0.003***	0.002**	0.003**
	(0.001)	(0.001)	(0.001)
Month/Year FE	Y	Y	Y
User FE	Y	N	Y
User trend	N	N	Y
Observations	22,669	22,669	22,669
R^2	0.012	0.012	0.034

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

A.6 References to Exile

References to exile itself increase in the months after leaving the country, providing greater confidence in the interpretation of findings. This is displayed in the figures and tables below.

Figure A7: Exile and Discussions of Exile
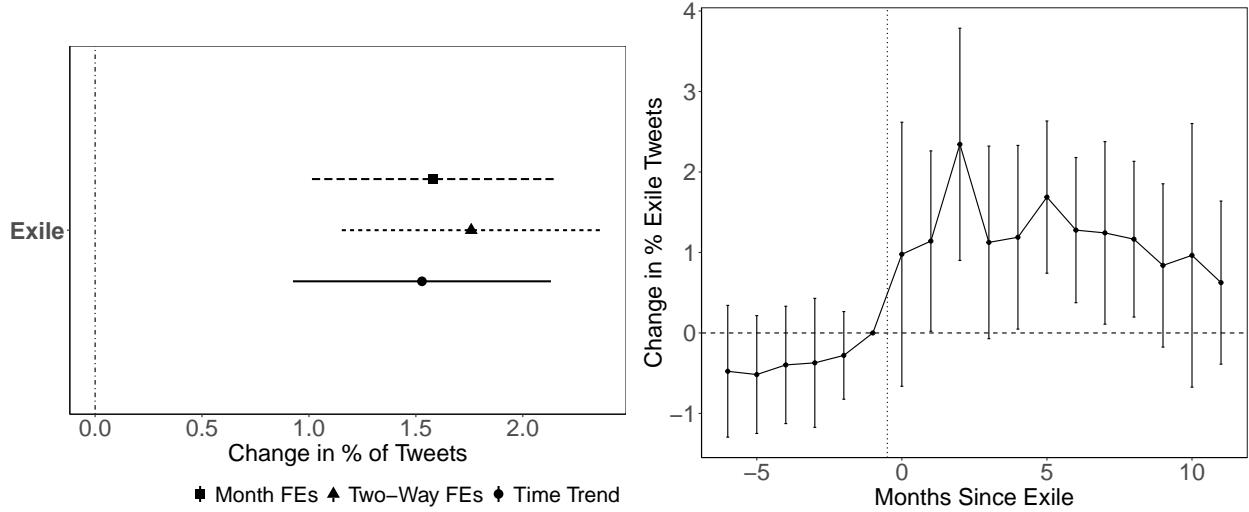
Tabular results for Figure A7 can be found in Table A10.

Table A10: Exile References and Exile

	Exile		
Tweeted from Exile	1.759***	1.581***	1.528***
	(0.309)	(0.289)	(0.308)
Number of Tweets	−0.023	−0.052**	0.003
	(0.029)	(0.023)	(0.022)
Month/Year FE	Y	Y	Y
User FE	Y	N	Y
User trend	N	N	Y
Observations	22,669	22,669	22,669
R^2	0.056	0.074	0.124

Note:	*p<0.1; **p<0.05; ***p<0.01
	Robust standard errors clustered at the user level.

A.7 Results by Location of Exile

The below figures and tables compares the effects for exiles in the US to exiles living elsewhere. There is no statistically detectable difference between the groups, which may be due to the sample being statistically underpowered when split, or be reflective of unity among the opposition abroad. Results are similar, but not shown, comparing exiles in Colombia to those elsewhere.

Figure A8: Effects by Destination Country
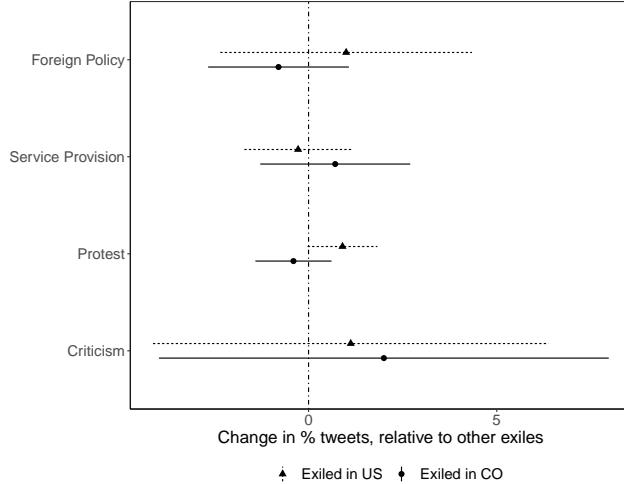
Tabular results for Figure A8 can be found in Table A11.

Table A11: Effects by Destination

|								
Tweeted from Exile	2.343***	−2.774***	−1.107***	5.605***	2.873***	−3.019***	−0.693**	5.615***
	(0.365)	(0.489)	(0.339)	(1.440)	(0.799)	(0.437)	(0.322)	(1.412)
Number of Tweets	0.110**	0.367***	0.286***	0.064	0.110**	0.367***	0.287***	0.066
	(0.050)	(0.086)	(0.071)	(0.175)	(0.049)	(0.086)	(0.071)	(0.175)
Tweeted from Exile*US Destination	0.999	−0.278	0.901*	1.120				
	(1.706)	(0.728)	(0.473)	(2.680)				
Tweeted from Exile * Colombia Destination					−0.798	0.708	−0.401	2.000
					(0.954)	(1.016)	(0.516)	(3.048)
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
User FEs	Y	N	Y	Y	N	Y	Y	N
User trend	N	N	Y	N	N	Y	N	N

Note:
*p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

A.8 T-Test Results

T-test results demonstrate that our results hold even in a simple descriptive setup. Our data include all tweets in our sample; we show the difference in the percent of tweets mentioning a topic in the 30, 60, or 120 days before and after an exile leaves Venezuela.

Figure A9: Pre-Post T-Tests
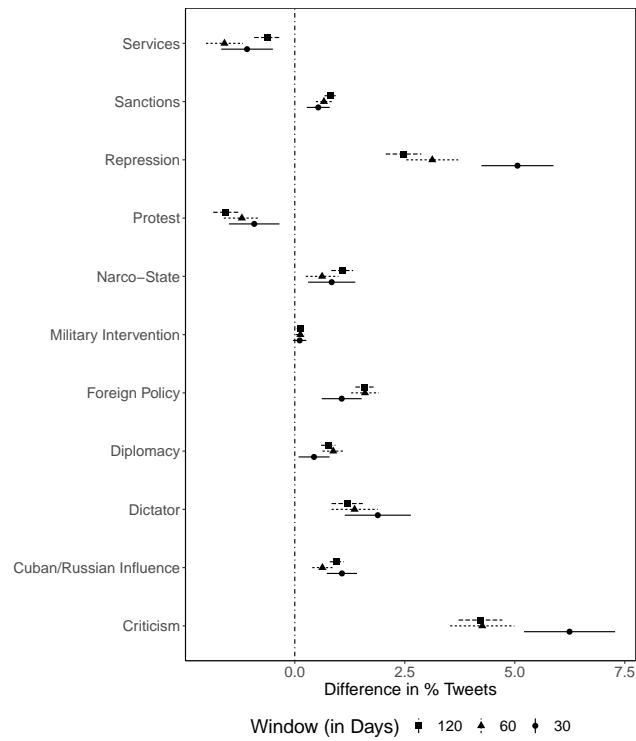
Tabular results for Figure A9 can be found in Table A12.

Table A12: T-test results (30, 60, and 120 windows)

Variable	Window	Estimate	CI (Low)	CI (High)	t-value	p-value
Foreign Policy	120.00	1.59	1.38	1.81	14.48	<.001
Foreign Policy	60.00	1.61	1.29	1.92	9.99	<.001
Foreign Policy	30.00	1.07	0.62	1.53	4.64	<.001
Military Intervention	120.00	0.12	0.05	0.20	3.13	<.001
Military Intervention	60.00	0.13	0.02	0.23	2.36	0.02
Military Intervention	30.00	0.11	-0.04	0.26	1.44	0.15
Sanctions	120.00	0.81	0.68	0.93	12.37	<.001
Sanctions	60.00	0.67	0.48	0.85	7.12	<.001
Sanctions	30.00	0.54	0.28	0.80	4.07	<.001
Diplomacy	120.00	0.76	0.59	0.92	9.06	<.001
Diplomacy	60.00	0.88	0.64	1.13	7.08	<.001
Diplomacy	30.00	0.44	0.09	0.79	2.44	0.01
Services	120.00	-0.63	-0.92	-0.34	-4.21	<.001
Services	60.00	-1.59	-2.01	-1.17	-7.38	<.001
Services	30.00	-1.06	-1.65	-0.47	-3.54	<.001
Protest	120.00	-1.56	-1.84	-1.27	-10.71	<.001
Protest	60.00	-1.21	-1.62	-0.80	-5.76	<.001
Protest	30.00	-0.92	-1.50	-0.35	-3.15	<.001
Harsh Criticism	120.00	4.25	3.75	4.75	16.67	<.001
Harsh Criticism	60.00	4.32	3.59	5.05	11.6	<.001
Harsh Criticism	30.00	6.27	5.23	7.30	11.86	<.001
Repression	120.00	2.53	2.13	2.94	12.24	<.001
Repression	60.00	3.20	2.61	3.79	10.62	<.001
Repression	30.00	5.08	4.27	5.90	12.16	<.001
Cuban/Russian Influence	120.00	0.95	0.79	1.12	11.56	<.001
Cuban/Russian Influence	60.00	0.64	0.40	0.87	5.4	<.001
Cuban/Russian Influence	30.00	1.09	0.75	1.43	6.22	<.001
Dictator	120.00	1.19	0.83	1.55	6.56	<.001
Dictator	60.00	1.37	0.84	1.89	5.1	<.001
Dictator	30.00	1.89	1.14	2.64	4.93	<.001
Narco-State	120.00	1.04	0.79	1.29	8.19	<.001
Narco-State	60.00	0.62	0.25	0.99	3.29	<.001
Narco-State	30.00	0.84	0.30	1.37	3.07	<.001

Appendix B: Robustness Checks

B.1   Including Inactive Months

In our main specifications, we do not include months where a Twitter account was dormant (e.g., where an activist did not tweet at all). Though we control for the number of tweets, the central purpose of this is to avoid conflating months where an elite did not tweet at all with those months where an elite did not tweet on a certain topic at all. Here we show that, with the exception of our results on protest, findings hold when using this alternative construction. Our findings on collective action thus remain weaker and more suspect than other results, though its robustness to other specifications does offer some reassurance.

Figure B1: Including Months with No Tweets
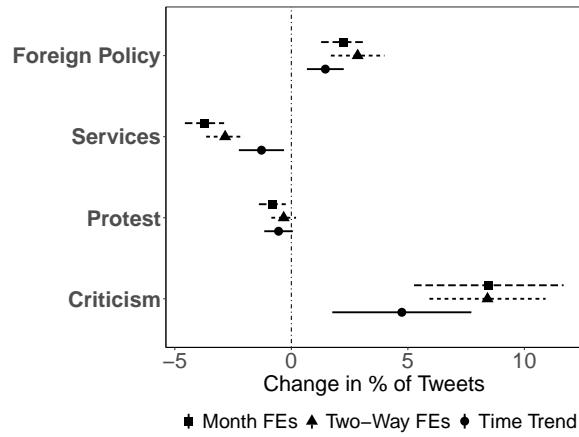
Tabular results for Figure B1 can be found in Table B1.

Table B1: Including Months With No Tweets

	Foreign Policy			Services		
Tweeted from Exile	2.845***	2.229***	1.459***	−2.841***	−3.727***	−1.281***
	(0.586)	(0.485)	(0.403)	(0.415)	(0.430)	(0.495)
Number of Tweets	0.248***	0.304***	0.200***	0.358***	0.286***	0.354***
	(0.034)	(0.021)	(0.030)	(0.085)	(0.093)	(0.081)
Observations	27,449	27,449	27,449	22,669	22,669	22,669
R²	0.145	0.156	0.251	0.198	0.190	0.266
	Protest			Criticism		
Tweeted from Exile	−0.328	−0.816***	−0.548*	8.419***	8.474***	4.741***
	(0.271)	(0.294)	(0.313)	(1.272)	(1.637)	(1.522)
Number of Tweets	0.676***	0.757***	0.699***	1.541***	2.052***	1.475***
	(0.048)	(0.040)	(0.053)	(0.140)	(0.132)	(0.152)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	27,449	27,449	27,449	27,449	27,449	27,449
R²	0.182	0.197	0.227	0.219	0.244	0.334

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors clustered at the user level.

B.2   Changing Event Study Estimation

The event study design in the paper compares exiles before and after leaving, and includes those never exiled in the 'pre' category. Because of the individual-level fixed effects, this is the equivalent of including all in-country activist-months in the base period $(−1)$, which we show here.

Figure B2: Foreign Policy
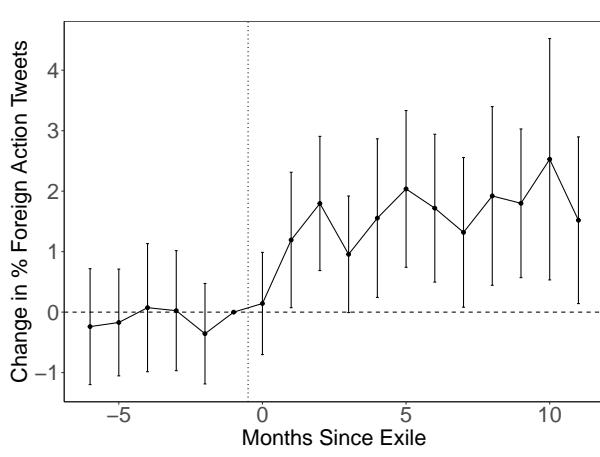
Figure B3: Services
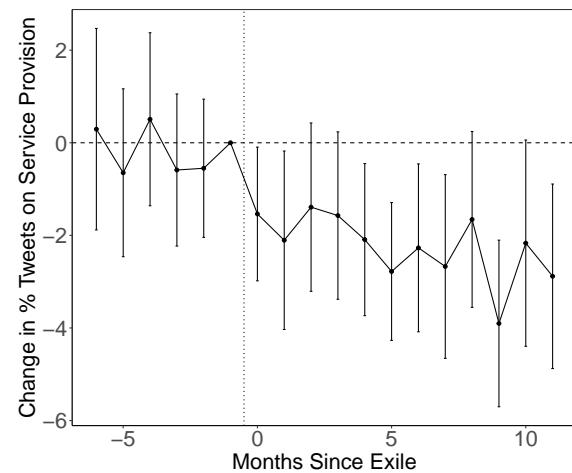
Figure B4: Protest
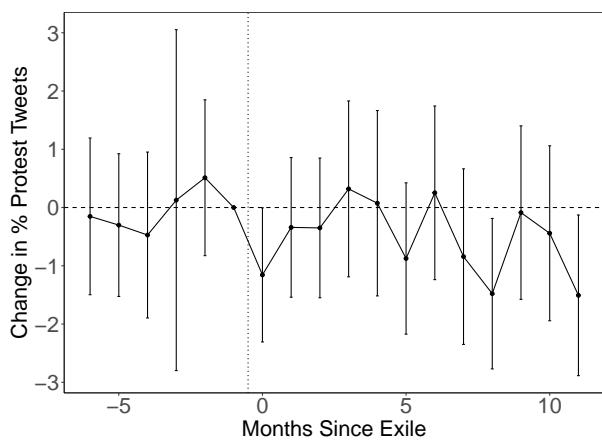
Figure B5: Harsh Criticism
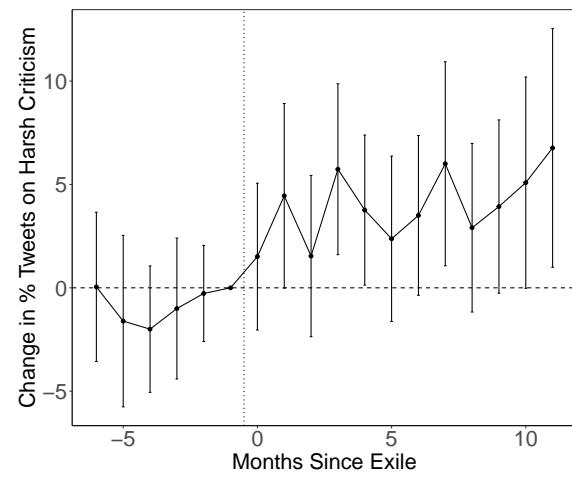
Tabular results for Figures B2-B5 can be found in Table A7.

B.3 Including Only Politicians

Our sample is non-exhaustive. In order to reduce any concerns that this may be driving our results, we show in Figures B6 and B7 that findings hold when restricting our analysis to the most complete set of activists – politicians elected to the National Assembly or as mayors in the last two election cycles. We additionally show our findings hold when using on politicians elected in 2011 or after, in case those elected earlier behave fundamentally different online.

Figure B6: Politicians Only
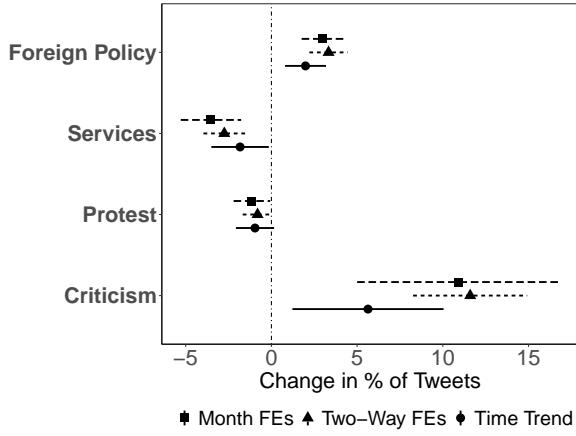
Figure B7: Politicians Elected after 2010 Only
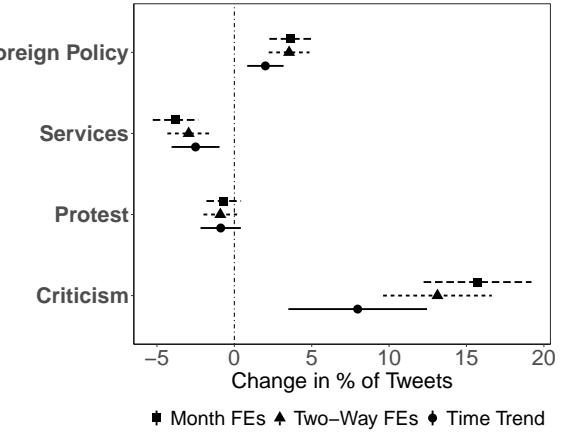
Tabular results for Figures B6 and B7 can be found in Tables B2 and B3.

Table B2: Including Only Politicians

	Foreign Policy			Services		
Tweeted from Exile	3.333***	2.998***	1.990***	−2.749***	−3.526***	−1.827**
	(0.571)	(0.630)	(0.609)	(0.619)	(0.898)	(0.855)
Number of Tweets	0.083	0.130**	0.070	0.571***	0.494***	0.523***
	(0.057)	(0.052)	(0.061)	(0.109)	(0.118)	(0.106)
Observations	15,232	15,232	15,232	15,232	15,232	15,232
R^2	0.158	0.157	0.206	0.240	0.230	0.298
	Protest			Criticism		
Tweeted from Exile	−0.808*	−1.139**	−0.957*	11.594***	10.903***	5.634**
	(0.442)	(0.545)	(0.569)	(1.698)	(3.011)	(2.248)
Number of Tweets	0.295***	0.344***	0.353***	0.410**	1.041***	0.257
	(0.099)	(0.086)	(0.108)	(0.204)	(0.230)	(0.215)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	15,232	15,232	15,232	15,232	15,232	15,232
R^2	0.227	0.213	0.276	0.285	0.266	0.378

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors clustered at the user level.

Table B3: Including Only Politicians Elected after 2010

	Foreign Policy			Services		
Tweeted from Exile	3.538***	3.648***	2.007***	−2.950***	−3.795***	−2.506***
	(0.673)	(0.707)	(0.600)	(0.702)	(0.753)	(0.790)
Number of Tweets	0.101*	0.139**	0.085*	0.573***	0.496***	0.492***
	(0.055)	(0.060)	(0.050)	(0.123)	(0.136)	(0.121)
Observations	11,973	11,973	11,973	11,973	11,973	11,973
R^2	0.171	0.170	0.223	0.261	0.255	0.317
	Protest			Criticism		
Tweeted from Exile	−0.905	−0.685	−0.880	13.125***	15.714***	7.969***
	(0.554)	(0.571)	(0.664)	(1.793)	(1.778)	(2.285)
Number of Tweets	0.290**	0.377***	0.328**	0.529**	1.127***	0.386*
	(0.120)	(0.102)	(0.128)	(0.216)	(0.263)	(0.228)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	11,973	11,973	11,973	11,973	11,973	11,973
R^2	0.240	0.224	0.289	0.316	0.304	0.402

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors clustered at the user level.

B.4 Political Prisoners

Maduro also uses detention of opponents to limit opposition. In case these periods of imprisonment precede exile, explaining results, we show here that findings hold when dropping those opponents who also served time in prison during the period of our sample B8 and when controlling for periods of imprisonment B9.

Figure B8: Excluding Political Prisoners
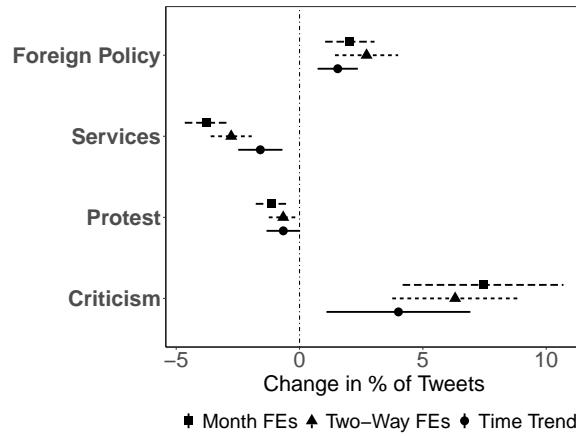
Figure B9: Controlling for Imprisonment
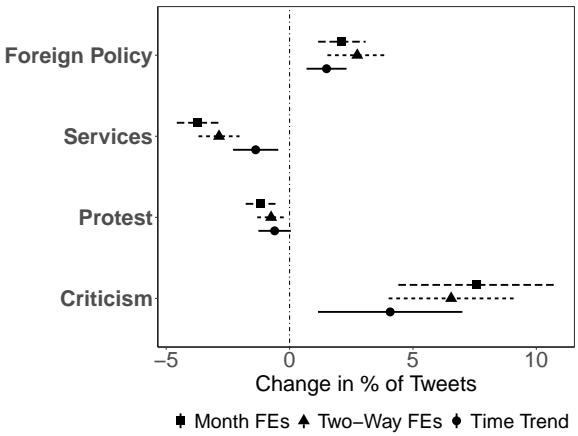
Tabular results for Figures B8 and B9 can be found in Tables B4 and B5.

Table B4: Excluding Political Prisoners

	Foreign Policy			Services		
Tweeted from Exile	2.717***	2.038***	1.548***	−2.770***	−3.779***	−1.589***
	(0.653)	(0.511)	(0.416)	(0.425)	(0.446)	(0.457)
Number of Tweets	0.129***	0.125***	0.098**	0.325***	0.263***	0.330***
	(0.047)	(0.043)	(0.042)	(0.085)	(0.094)	(0.081)
Observations	22,007	22,007	22,007	22,007	22,007	22,007
R^2	0.160	0.152	0.266	0.197	0.190	0.264
	Protest			Criticism		
Tweeted from Exile	−0.661**	−1.149***	−0.658*	6.308***	7.439***	4.008***
	(0.299)	(0.319)	(0.347)	(1.301)	(1.664)	(1.488)
Number of Tweets	0.273***	0.263***	0.375***	0.147	0.752***	0.269*
	(0.072)	(0.069)	(0.079)	(0.169)	(0.197)	(0.154)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,007	22,007	22,007	22,007	22,007	22,007
R^2	0.201	0.185	0.252	0.233	0.208	0.342

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors clustered at the user level.

Table B5: Controlling for Political Imprisonment

	Foreign Policy			Services		
Tweeted from Exile	2.743***	2.119***	1.498***	−2.860***	−3.729***	−1.375***
	(0.618)	(0.491)	(0.414)	(0.424)	(0.430)	(0.468)
Number of Tweets	0.042	0.695	−0.173	−1.384	−0.700	−2.228
	(1.540)	(0.805)	(1.692)	(1.750)	(0.690)	(1.586)
log(num_tweets + 1)	0.109**	0.122***	0.089**	0.351***	0.284***	0.339***
	(0.048)	(0.043)	(0.043)	(0.084)	(0.093)	(0.080)
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.161	0.154	0.265	0.199	0.190	0.267
	Protest			Criticism		
Tweeted from Exile	−0.748***	−1.175***	−0.606*	6.548***	7.593***	4.076***
	(0.288)	(0.308)	(0.336)	(1.292)	(1.625)	(1.493)
Number of Tweets	−0.197	1.075	0.291	12.970***	24.523***	13.690***
	(1.102)	(1.059)	(1.067)	(5.026)	(5.754)	(5.230)
log(num_tweets + 1)	0.288***	0.273***	0.377***	0.124	0.703***	0.259*
	(0.071)	(0.068)	(0.078)	(0.172)	(0.196)	(0.153)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,669	22,669	22,669	22,669	22,669	22,669
R^2	0.203	0.188	0.254	0.238	0.223	0.350

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.

21

B.5 Political Party

Opposition parties in Venezuela range hardline to open to negotiating with the Maduro regime; because of this, members of the opposition likely differ both in preferences and in their likelihood of being exiled. To account for this, we show results controlling for party ID interacted with a time trend, and showing results only for Guaidó's *Voluntad Popular* (VP). Results largely hold, though the findings on protest become noisier, particularly when subsetting to only VP.

<div style="display: flex;">

Figure B10: Controlling for party ID
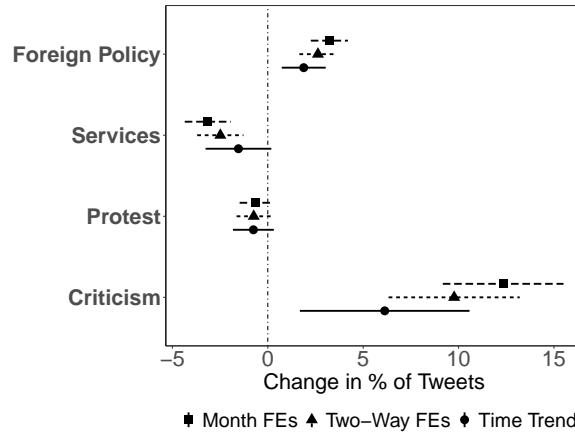
Figure B11: Including only VP

</div>
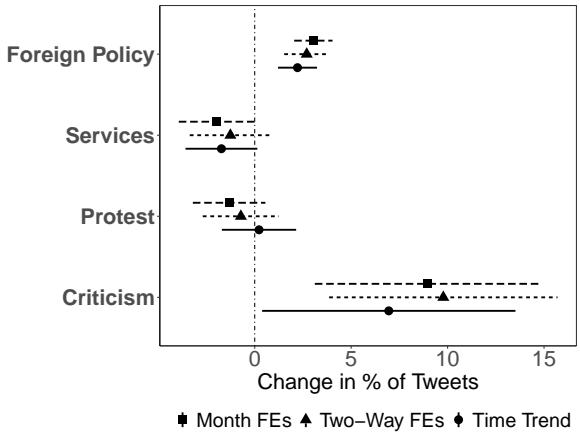
Tabular results for Figures B10 and B11 can be found in Tables B6 and B7.

Table B6: Controlling for Party

	Foreign Policy			Services		
Tweeted from Exile	2.630***	3.228***	1.884***	−2.487***	−3.143***	−1.538*
	(0.497)	(0.496)	(0.589)	(0.619)	(0.617)	(0.879)
Number of Tweets	0.095*	0.138***	0.077	0.595***	0.515***	0.497***
	(0.057)	(0.042)	(0.061)	(0.104)	(0.118)	(0.107)
Observations	15,240	15,240	15,240	15,240	15,240	15,240
R^2	0.176	0.190	0.205	0.250	0.255	0.295
	Protest			Criticism		
Tweeted from Exile	−0.737	−0.662	−0.754	9.769***	12.337***	6.129***
	(0.459)	(0.416)	(0.546)	(1.754)	(1.614)	(2.268)
Number of Tweets	0.325***	0.334***	0.347***	0.299	0.883***	0.215
	(0.100)	(0.088)	(0.107)	(0.203)	(0.229)	(0.217)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	15,240	15,240	15,240	15,240	15,240	15,240
R^2	0.236	0.240	0.275	0.317	0.347	0.377

Note: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Robust standard errors clustered at the user level.

Table B7: Only Voluntad Popular Members

	Foreign Policy			Services		
Tweeted from Exile	2.697***	3.039***	2.218***	−1.261	−1.966*	−1.726*
	(0.596)	(0.507)	(0.516)	(1.075)	(1.006)	(0.950)
Number of Tweets	−0.114	0.183*	0.073	0.690**	0.690	0.399
	(0.160)	(0.109)	(0.139)	(0.280)	(0.432)	(0.315)
Observations	2,047	2,047	2,047	2,047	2,047	2,047
R^2	0.299	0.323	0.344	0.265	0.252	0.314

	Protest			Criticism		
Tweeted from Exile	−0.717	−1.327	0.223	9.778***	8.980***	6.950**
	(1.008)	(0.959)	(0.983)	(3.020)	(2.992)	(3.351)
Number of Tweets	0.439	0.731***	0.322	−0.370	0.668	−0.180
	(0.305)	(0.238)	(0.253)	(0.518)	(1.151)	(0.595)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	2,047	2,047	2,047	2,047	2,047	2,047
R^2	0.319	0.305	0.397	0.427	0.342	0.479

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors clustered at the user level.

B.6   Robustness to Dropping Individuals

The following show that our results are consistent when dropping each individual user in turn. This provides greater confidence that results are not being driven by a small number of cases having disproportionate influence on findings. Figures below show the estimates for the model with one activist dropped, with confidence intervals in gray.

Figure B12: Foreign Policy   Figure B13: Service Provision
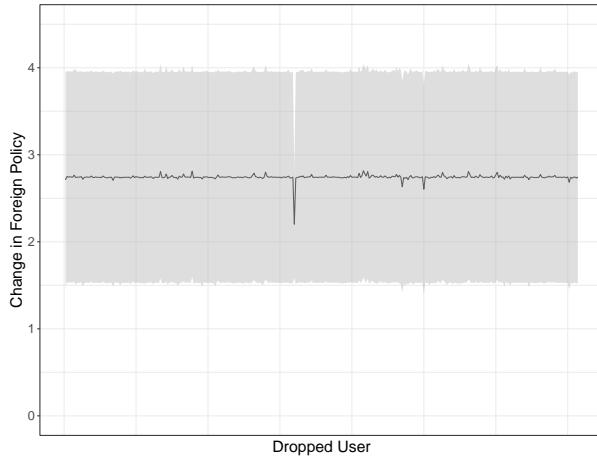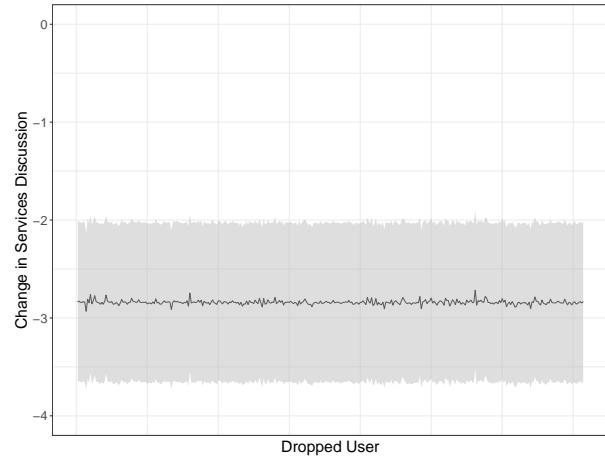
Figure B14: Protest
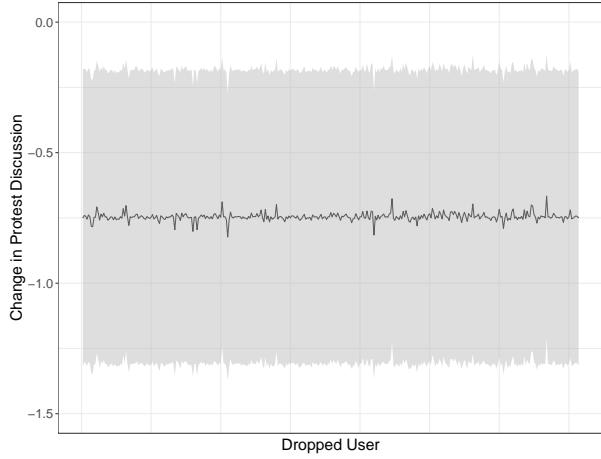
Figure B15: Harsh Criticism
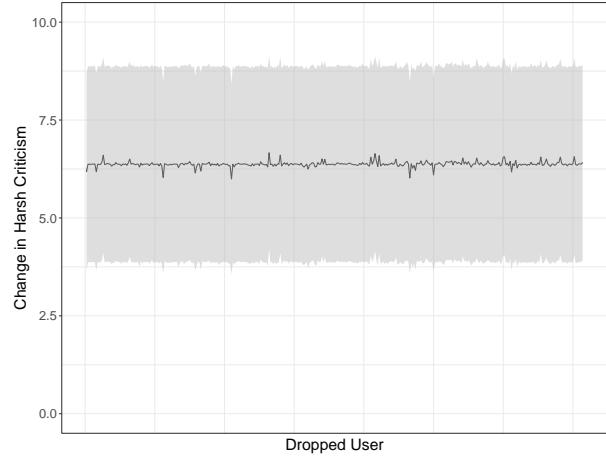
B.7 Goodman-Bacon Decomposition

Recent research has also raised concerns about the causal interpretation of two-way fixed effects difference-in-differences designs with staggered treatment timing when effects are heterogenous across time (which is often likely to be the case) (Goodman-Bacon 2021; Imai and Kim 2020). The central concern is that negative weights may be assigned when treatment effects and timing vary because already-treated units may serve as control groups. This is of somewhat less concern in our design because our sample of never-treated individuals is large, but we nonetheless conduct Goodman-Bacon decomposition for each of our four main outcomes. We show here that our estimates are similar regardless of the timing of treatment, and weights are similar across treatment periods.

B.8 Callaway and Sant'Anna

In this section, we show results using the Callaway and Sant'Anna DD estimator, which can be used to address concerns of bias in difference- in-differences designs with staggered treatment timing. Figure B18 shows the summary results for each dependent variable, while Figures B19 to B22 show event studies. Results are robust to using this alternative estimator, except for harsh criticism, which is substantively stable but is not statistically significant. Breaking the data down by time shows that results are stronger for the period 2016 and after. Our descriptive results in Appendix A suggest that this may be due to these criticisms becoming more salient as Maduro consolidates power.

Figure B16: Goodman-Bacon Decomposition Plots

Foreign Policy

Protest

Harsh Criticism

Service Provision
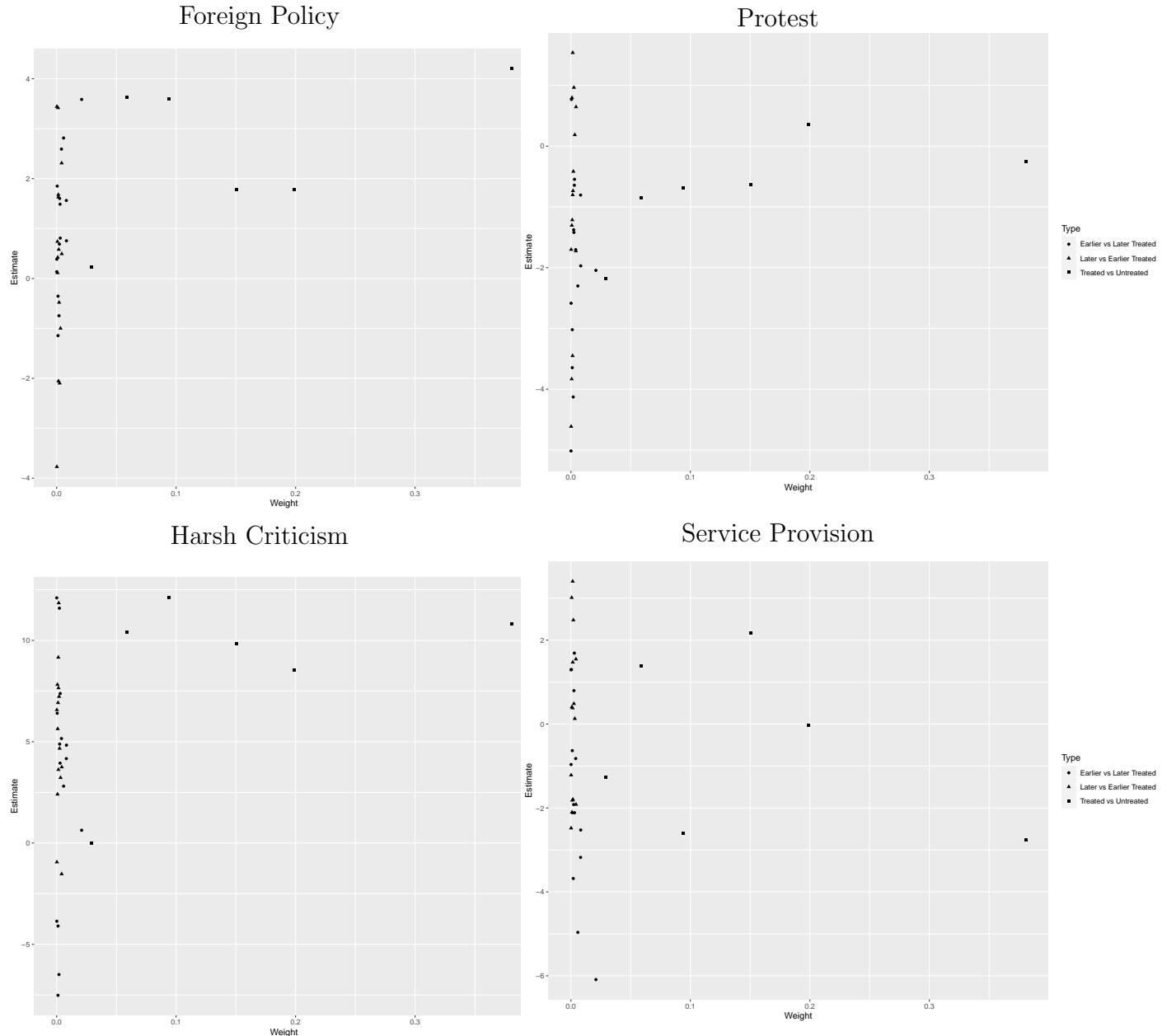
Figure B17: Goodman-Bacon Decomposition Tables

Foreign Policy

Type	Average Estimate	Number of 2x2 Comparisons	Total Weight
Earlier vs Later Treated	1.07	15	0.06
Later vs Earlier Treated	0.36	15	0.03
Treated vs Untreated	2.54	6	0.91

Harsh Criticism

Type	Average Estimate	Number of 2x2 Comparisons	Total Weight
Earlier vs Later Treated	2.79	15	0.06
Later vs Earlier Treated	5.20	15	0.03
Treated vs Untreated	8.62	6	0.91

Protest

Type	Average Estimate	Number of 2x2 Comparisons	Total Weight
Earlier vs Later Treated	-2.03	15	0.06
Later vs Earlier Treated	-1.04	15	0.03
Treated vs Untreated	-0.71	6	0.91

Service Provision

Type	Average Estimate	Number of 2x2 Comparisons	Total Weight
Earlier vs Later Treated	-1.5947	15	0.0624
Later vs Earlier Treated	0.1324	15	0.0260
Treated vs Untreated	-0.5138	6	0.9116

Table B8: Callaway and Sant'Anna Estimators

Variable	ATT	Std. Error	95% CI (min)	95% CI (max)
Foreign Policy	3.041	0.5476	1.9676	4.1144
Service Provision	-2.765	0.7893	-4.312	-1.218
Protest	-2.297	0.466	-3.210	-1.384
Harsh Criticism	3.759	2.930	-1.983	9.502
Harsh Criticism 2016	4.555	2.088	0.464	8.647

Figure B18: Callaway and Sant'Anna estimator
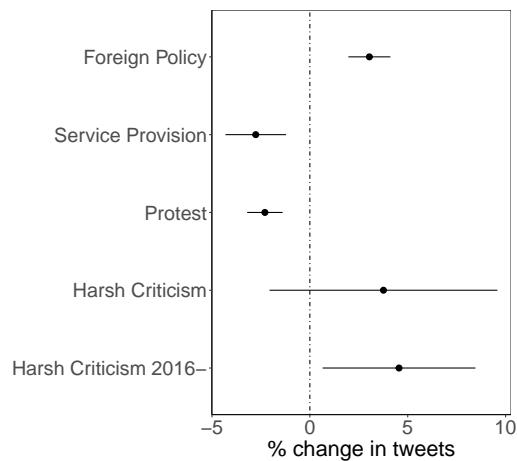
*Tabular results for Figure B18 can be found in Table B8.*

Figure B19: Foreign Policy
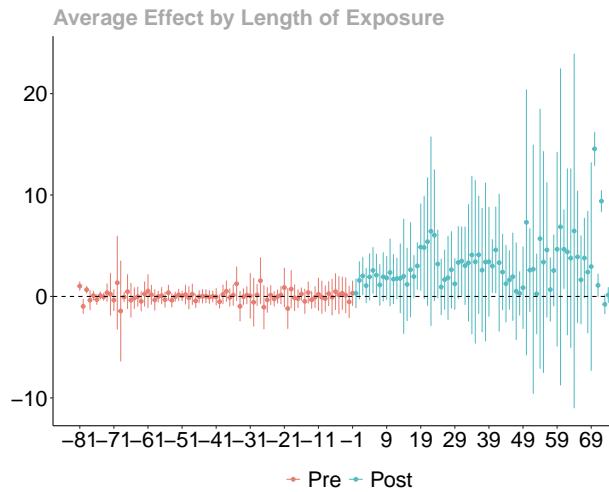

Figure B20: Service Provision

Figure B21: Protest

Average Effect by Length of Exposure
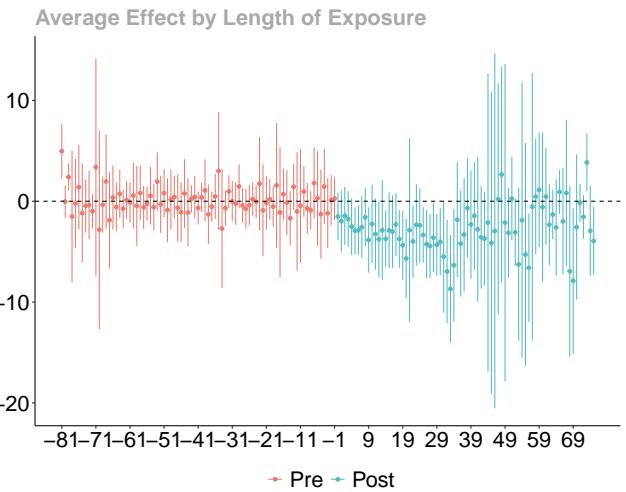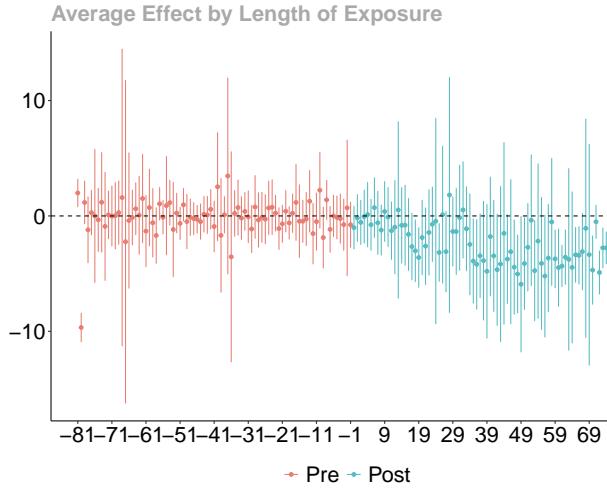
Figure B22: Harsh Criticism

Average Effect by Length of Exposure
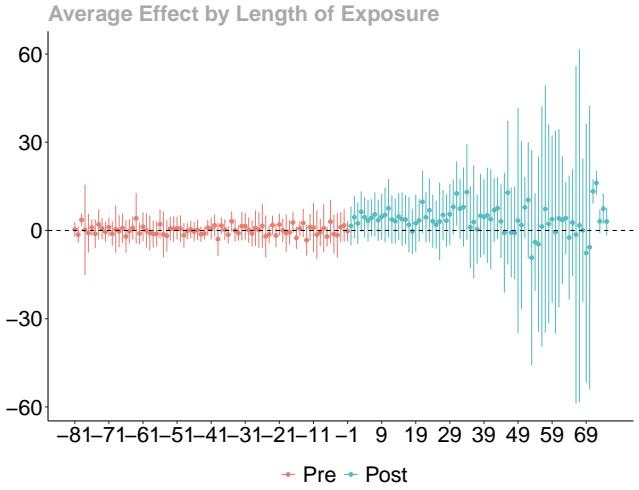
Figure B23: Harsh Criticism 2016-

Average Effect by Length of Exposure
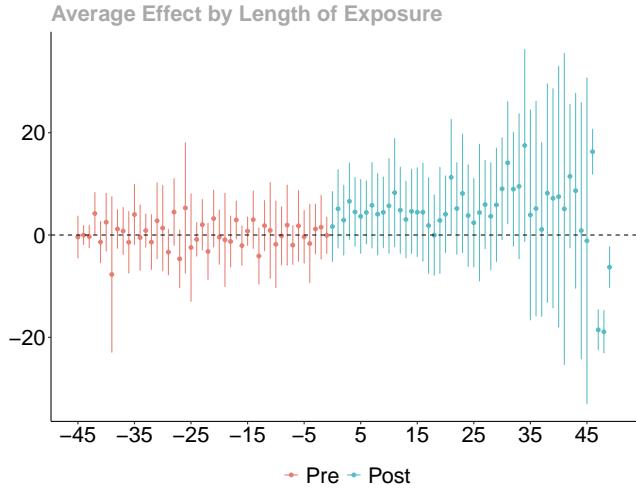

B.9 Removing Early Exiles

Concerns about the causal interpretation of two-way fixed effects models with staggered treatment timing are driven primarily by the use of earlier treated units as a comparison group for later treated units. While the nature of our sample, which includes many never-treated individuals, reduces these concerns somewhat, we additionally show our results hold when excluding those individuals exiled prior to the beginning of our Twitter data in 2013 and including only those exiled later in the regime (excluding those exiled before 2017) (Figures B24 and B25 and Tables B9 and B10).

28

Figure B24: Excluding Early Exiles (pre-2013)   Figure B25: Excluding Early Exiles (pre-2017)
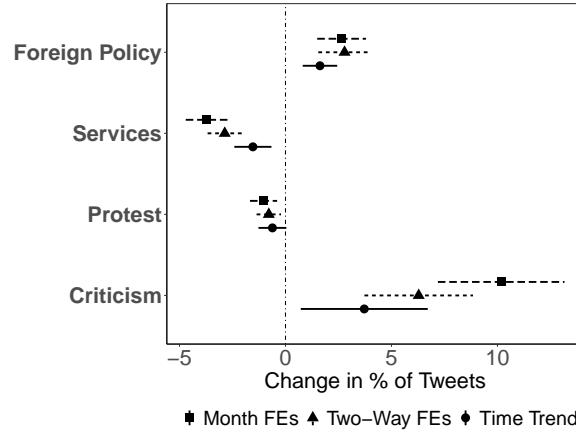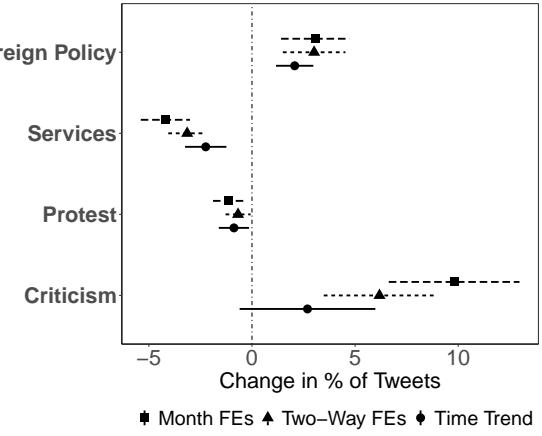
Tabular results for Figures B24 and B25 can be found in Tables B9 and B10.

Table B9: Exiled After 2013

	Foreign Policy			Services		
Tweeted from Exile	2.785***	2.647***	1.627***	−2.865***	−3.708***	−1.537***
	(0.631)	(0.587)	(0.415)	(0.413)	(0.508)	(0.447)
Number of Tweets	0.126***	0.138***	0.110***	0.346***	0.285***	0.335***
	(0.046)	(0.043)	(0.042)	(0.084)	(0.095)	(0.080)
Observations	22,027	22,027	22,027	22,027	22,027	22,027
R^2	0.164	0.162	0.270	0.200	0.189	0.265

	Protest			Criticism		
Tweeted from Exile	−0.786***	−1.035***	−0.616*	6.284***	10.175***	3.716**
	(0.294)	(0.327)	(0.336)	(1.306)	(1.524)	(1.528)
Number of Tweets	0.290***	0.265***	0.370***	0.102	0.738***	0.213
	(0.071)	(0.070)	(0.079)	(0.173)	(0.207)	(0.161)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	22,027	22,027	22,027	22,027	22,027	22,027
R^2	0.204	0.188	0.254	0.240	0.221	0.350

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$

Robust standard errors clustered at the user level.

Table B10: Exiled After 2017

	Foreign Policy			Services		
Tweeted from Exile	3.014***	3.069***	2.071***	−3.142***	−4.200***	−2.242***
	(0.774)	(0.845)	(0.463)	(0.468)	(0.608)	(0.511)
Number of Tweets	0.094**	0.124***	0.086**	0.378***	0.288***	0.370***
	(0.045)	(0.043)	(0.042)	(0.087)	(0.099)	(0.081)
Observations	20,934	20,934	20,934	20,934	20,934	20,934
R^2	0.154	0.153	0.257	0.204	0.192	0.269

	Protest			Criticism		
Tweeted from Exile	−0.675**	−1.144***	−0.874**	6.183***	9.802***	2.692
	(0.310)	(0.381)	(0.374)	(1.378)	(1.617)	(1.679)
Number of Tweets	0.295***	0.261***	0.357***	0.122	0.755***	0.200
	(0.073)	(0.072)	(0.082)	(0.167)	(0.207)	(0.163)
Month/Year FE	Y	Y	Y	Y	Y	Y
User FE	Y	N	Y	Y	N	Y
User trend	N	N	Y	N	N	Y
Observations	20,934	20,934	20,934	20,934	20,934	20,934
R^2	0.206	0.189	0.256	0.238	0.213	0.348

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered at the user level.