

Web Appendix 1 References for Appendix 1

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Web Appendix 2

Transcript sources

August 2015 GOP debate:

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February 2016 GOP debate:

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New York Times staff (2016, March 4). Transcript of the Republican Presidential Debate in Detroit, *The New York Times*. Retrieved from <https://www.nytimes.com>. Link: <https://www.nytimes.com/2016/03/04/us/politics/transcript-of-the-republican-presidential-debate-in-detroit.html>

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Web Appendix 3: Topic clusters

Table WA3-1: Policy Topics

Cluster	Illustrative Keywords
Asia	China, Japan, Korea, India
Europe	England, Russia, Ukraine, NATO
Middle East	Arab, Afghanistan, Iran, Israel
Terrorism	Terrorists, Qaida, ISIS,
Defense	Army, Military, Defense
Education	Education, Schools, Pell
Immigration, Latin America	Mexico, border, citizenship
Healthcare	Obamacare, mandate, premiums
Economy	Jobs, spending, deficit, TARP
Courts	Supreme Court, Judge, Laws
Abortion	Roe, Parenthood, Prolife
Environment	Climate, environment, warming

Table WA3-2: Contentious Exchanges

Event	Illustrative Keywords
August 2015 exchange between moderator Megyn Kelly and Donald Trump over his views toward women	Megyn Kelly, Rosie, Apprentice
February 2016 exchange between candidate Ted Cruz and Donald Trump on the topic of lying	Lyin' Ted, Lies
March 2016 exchange between candidate Marco Rubio and Donald Trump over having "small hands"	Small Hands
March 2016 exchange between Megyn Kelly and Donald Trump over his complicity in lawsuits involving Trump University	Trump University, Plaintiffs, Better Business Bureau
Donald Trump's reference to some Mexican immigrants as "bad hombres" in the Presidential debate.	Bad Hombres
Hillary Clinton defending herself from Donald Trump's allegations that she destroyed emails in the Presidential debate	Emails, Server
Donald Trump describing Hillary Clinton as a "nasty woman" in the Presidential debate.	Nasty Woman

Web Appendix 4
Pearson Correlations Between User Bot Probabilities and Retweet Counts and Tweet Characteristics (N=31,524 users)

Feature	r/Prob r
Total Retweets	0.002
	0.671
Policy Topic	0.008
	0.182
Contentious exchange	-0.007
	0.212
Appearance	0.004
	0.468
Abstract Theme	0.000
	0.960
Humor	0.003
	0.627
Graphics	-0.007
	0.205
Word Count	0.002
	0.679
Pos Emotion	0.005
	0.344
Neg Emotion	0.002
	0.770
Achievement words	0.001
	0.889
Power Words	-0.004
	0.500
Reward Words	-0.005
	0.342
Informal Words	0.002
	0.692
Percent Subjective	0.007
	0.199
Specificity	-0.006
	0.325
Quote	-0.006
	0.303
Donald Trump	-0.005
	0.369

Web Appendix 5

Correlation Matrix of Predictors used in Retweet Regressions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	
(1) Log Followers	1.00																		
(2) Debate Tweets	0.19	1.00																	
	<.0001																		
(3) Word Count	0.09	0.04	1.00																
	<.0001	<.0001																	
(4) Graphics	0.09	0.02	0.06	1.00															
	<.0001	<.0001	<.0001																
(5) Quotes	0.02	0.00	-0.06	-0.03	1.00														
	<.0001	<.0001	<.0001	<.0001															
(6) Appearance	0.00	-0.01	0.16	-0.04	0.00	1.00													
	0.15	<.0001	<.0001	<.0001	<.0001														
(7) Specificity	0.11	0.10	0.17	0.09	0.08	-0.02	1.00												
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001													
(8) Analytic Style	0.06	0.01	0.00	0.10	-0.06	-0.06	0.20	1.00											
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001												
(9) Authentic Style	-0.03	-0.05	0.04	-0.10	0.01	0.03	-0.08	-0.04	1.00										
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001											
(10) Pos Emotion	-0.02	-0.02	-0.03	-0.08	0.01	0.05	-0.03	-0.02	-0.05	1.00									
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001										
(11) Neg Emotion	-0.04	0.00	-0.08	-0.08	0.07	-0.02	0.02	-0.03	-0.08	-0.08	1.00								
	<.0001	0.00	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001									
(12) Achievement	0.00	0.00	0.05	-0.04	-0.01	0.01	-0.01	0.00	0.00	0.18	0.02	1.00							
	0.86	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001								
(13) Power	-0.01	0.01	0.06	-0.07	0.01	-0.01	0.04	0.05	0.04	0.07	0.06	0.18	1.00						
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001							
(14) Reward	-0.01	-0.02	0.01	-0.05	-0.01	0.01	-0.06	0.00	-0.02	0.29	-0.05	0.28	0.07	1.00					
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001						
(15) Policy	0.03	0.06	0.14	-0.03	0.04	0.00	0.07	0.01	-0.02	-0.01	0.00	0.03	0.05	-0.01	1.00				
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001					
(16) Contentious	0.01	0.01	0.09	-0.01	0.07	0.02	0.02	-0.04	-0.04	0.00	0.10	-0.03	0.05	-0.03	0.09	1.00			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
(17) Abstract Theme	0.01	0.01	0.07	-0.01	0.00	0.02	0.00	0.01	0.02	0.00	-0.02	0.03	0.03	-0.01	0.06	0.01	1.00		
	<.0001	<.0001	<.0001	<.0001	0.15	<.0001	0.01	<.0001	<.0001	0.16	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
(18) Trump	0.03	0.04	0.16	-0.01	0.03	0.03	0.09	0.00	-0.04	-0.03	0.01	0.02	0.01	-0.01	0.06	0.05	0.00	1.00	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Web Appendix 6: Tweet features by Users Posting during and After the Debate

Category	Measure		LS Mean	Lower 95%	Upper 95%
Surface Features	Word Count	After	15.99	15.97	16.02
		During	14.65	14.64	14.67
	%Video or Photo	After	9.02	8.92	9.11
		During	6.84	6.78	6.89
	%Quotes	After	1.62	1.59	1.65
During		2.64	2.62	2.66	
Linguistic Style	Specificity	After	0.43	0.43	0.43
		During	0.40	0.40	0.40
	Analytic	After	78.87	78.75	79.00
		During	74.96	74.88	75.03
	Authentic	After	23.34	23.21	23.47
During		24.60	24.52	24.67	
LIWC Emotion and Drive	Positive Emotion	After	3.82	3.80	3.85
		During	3.12	3.11	3.13
	Negative Emotion	After	2.57	2.55	2.60
		During	2.79	2.77	2.80
	%Achievement	After	1.59	1.58	1.60
		During	1.15	1.15	1.16
	%Reward	After	1.68	1.67	1.69
During		1.29	1.28	1.30	
% Power	After	2.93	2.91	2.95	
	During	2.96	2.95	2.97	
Topic	%Policy	After	4.93	4.79	5.06
		During	13.43	13.35	13.51
	%Contentious Exchange	After	7.58	7.48	7.69
		During	5.57	5.51	5.63
	%Abstract Theme	After	1.73	1.68	1.79
		During	1.95	1.92	1.99
Appearance or Expression	After	13.66	13.53	13.80	
	During	12.97	12.89	13.04	

Table WA6: Mean features of Tweets created during versus after debate by users who created Tweets in both phases. All contrasts are significant at $p < .0001$

Web Appendix 7

Model Robustness Checks

Table WA7-1

Comparison of Negative Binomial, Poisson, and Log Linear Models of Retweet Counts During the Debates

	Predictor	Negative Binomial		Poisson		Log Linear	
		Estimate	SE	Estimate	SE	Estimate	SE
User Features	log(followers)	0.350	0.000	0.513	0.000	0.133	0.000
	User Tweets	-0.001	0.000	-0.003	0.000	0.000	0.000
Surface Features	Word Count	0.017	0.000	0.018	0.000	0.007	0.000
	Graphics	0.372	0.003	0.230	0.001	0.167	0.001
	Quote	0.002	0.000	0.002	0.000	0.001	0.000
Linguistic Style	Specificity	-0.010	0.003	-0.036	0.001	-0.018	0.001
	Analytic	0.000	0.000	-0.157	0.001	0.005	0.001
	Authentic	0.000	0.000	-0.002	0.000	0.000	0.000
LIWC Emotion and Drive	Pos Emotion	0.000	0.000	0.000	0.000	0.000	0.000
	Neg Emotion	0.002	0.000	0.000	0.000	0.000	0.000
	Achievement	0.005	0.000	0.006	0.000	0.001	0.000
	Power	0.005	0.000	0.008	0.000	0.001	0.000
	Reward	-0.002	0.000	0.010	0.000	0.002	0.000
Topic	Policy Topic	0.081	0.002	-0.003	0.000	-0.001	0.000
	Cont. Exchange	0.132	0.003	0.108	0.001	0.036	0.001
	Abstract Theme	0.017	0.006	0.243	0.001	0.053	0.001
	Appearance	-0.034	0.002	0.028	0.003	0.022	0.003
Controls	Trump	0.036	0.002	-0.040	0.001	0.016	0.001
	Aug Debate	-0.006	0.002	-0.048	0.001	0.003	0.001
	Feb Debate	-0.022	0.002	-0.106	0.001	0.009	0.001
	March Debate	-0.011	0.002	-0.105	0.001	0.014	0.001
Model	Intercept	-1.894	0.003	-2.866	0.002	-0.685	0.001
	Dispersion	0.462	0.001				
		LL	-4754548	LL	-9098823	R ²	0.219

Table WA7-2

Negative Binomial Regression Model of Retweets During the Debates, Estimated with and Without Candidate Fixed Effects

	Predictor	With Fixed Effects		Without Fixed Effects	
		Estimate	SE	Estimate	SE
User Feat	log(followers)	0.350	0.000	0.351	0.000
	User Tweets	-0.001	0.000	-0.001	0.000
Surface Fe	Word Count	0.017	0.000	0.017	0.000
	Graphics	0.372	0.003	0.364	0.003
	Quote	0.002	0.000	0.002	0.000
Linguistic	Specificity	-0.010	0.003	-0.042	0.002
	Analytic	0.000	0.000	-0.001	0.002
	Authentic	0.000	0.000	0.000	0.000
LIWC Emotion and Drive	Pos Emotion	0.000	0.000	0.000	0.000
	Neg Emotion	0.002	0.000	-0.001	0.000
	Achievement	0.005	0.000	0.001	0.000
	Power	0.005	0.000	0.004	0.000
	Reward	-0.002	0.000	0.004	0.000
Topic	Policy Topic	0.081	0.002	-0.003	0.000
	Cont. Exchange	0.132	0.003	0.080	0.002
	Abstract Theme	0.017	0.006	0.142	0.002
	Appearance	-0.034	0.002	0.037	0.005
Controls	Trump	0.036	0.002		
	Aug Debate	-0.006	0.002		
	Feb Debate	-0.022	0.002		
	March Debate	-0.011	0.002		
Model	Intercept	-1.894	0.003	-1.881	0.003
	Dispersion	0.462	0.001	0.452	0.001

Table WA7-3

Negative Binomial Regression Model of Retweets During and After the Debates, Estimated with Disaggregate Policy Topics

Parameter	During			After			Change	
	Estimate	Std Error	t value	Estimate	Std Error	t value	Estimate	t value
Intercept	-1.866	0.003	-705.680	-9.110	0.024	-384.390	-7.243	-303.741
log(followers)	0.351	0.000	1336.340	0.757	0.002	327.480	0.406	174.5813
user_tweets	-0.001	0.000	-58.940	-0.005	0.000	-33.070	-0.003	-24.3638
immigration	0.035	0.004	9.950	-0.324	0.027	-12.150	-0.358	-13.3525
terrorism	0.059	0.006	9.150	-0.089	0.048	-1.880	-0.148	-3.09275
economy	0.046	0.004	11.500	-0.321	0.030	-10.810	-0.367	-12.2419
health	-0.012	0.009	-1.360	0.416	0.062	6.690	0.428	6.813248
courts	0.065	0.006	10.580	-0.345	0.046	-7.420	-0.410	-8.7521
abortion	0.175	0.005	34.480	-0.204	0.038	-5.330	-0.379	-9.796
Asia	0.032	0.008	4.290	0.140	0.057	2.440	0.107	1.859963
Europe	0.079	0.004	18.820	-0.598	0.033	-18.380	-0.677	-20.6244
MiddleEast	-0.003	0.006	-0.540	-0.091	0.046	-1.970	-0.088	-1.87877
Environment	0.138	0.011	12.660	1.526	0.076	20.190	1.388	18.17928
Defense	0.031	0.009	3.550	0.254	0.061	4.160	0.223	3.609117
Education	0.033	0.009	3.600	0.438	0.063	7.000	0.405	6.401508
Contentious	0.136	0.002	55.920	0.859	0.017	50.370	0.723	41.98689
Appearance	-0.036	0.002	-18.080	-0.164	0.015	-11.290	-0.129	-8.76565
Abstract Theme	0.026	0.005	5.280	0.119	0.036	3.310	0.093	2.569346
humor	-0.027	0.004	-6.440	-0.490	0.033	-14.750	-0.463	-13.8217
graphics	0.414	0.003	158.020	1.490	0.018	81.710	1.076	58.4327
word count	0.015	0.000	132.640	0.073	0.001	81.910	0.058	64.09211
posemo	0.001	0.000	4.840	0.007	0.001	6.200	0.006	5.561293
negemo	0.003	0.000	23.080	0.003	0.001	3.230	0.000	0.364454
achievement	0.003	0.000	13.830	0.056	0.002	32.670	0.053	30.5915
power	0.004	0.000	28.690	0.015	0.001	15.150	0.011	11.25573
reward	-0.003	0.000	-15.600	0.023	0.002	14.010	0.027	15.83976
informal	-0.007	0.000	-58.530	-0.007	0.001	-7.210	0.000	0.25972
% subjective	-0.001	0.000	-9.530	-0.007	0.000	-15.850	-0.007	-14.5085
specificity	0.010	0.002	4.190	0.567	0.016	34.540	0.558	33.64206
Quote	0.002	0.000	19.880	-0.004	0.001	-6.010	-0.006	-8.47573
Controls								
Trump	0.019	0.001	13.480	-0.035	0.011	-3.280	-0.054	-5.03747
debate aug	-0.032	0.002	-19.430	-0.205	0.013	-16.240	-0.172	-13.5486
debate feb	-0.033	0.002	-15.820	-0.422	0.016	-26.620	-0.389	-24.313
debate mar	-0.023	0.002	-10.460	-0.122	0.016	-7.510	-0.099	-6.02526
debate pres	0.000	.	.	0.000	.	.		
Dispersion	0.452	0.001	774.230	26.451	0.134	197.730	25.999	194.3515
Model Fit								
LL	-4752446			-503324				
AIC	9504963			1006721				
SBC	9505426			1007183				

Web Appendix 8:
Negative Binomial Regression of retweets of Tweets created after the debate

	Parameter	Estimate	Standard Error	t Value	Pr > t
User Features	log(followers)	0.352	0.001	507.28	<.0001
	User Tweets	-0.001	0.000	-24.42	<.0001
Surface Features	Word Count	0.010	0.000	31.12	<.0001
	Graphics	0.441	0.006	73.01	<.0001
	Quote	0.003	0.000	9.29	<.0001
Linguistic Style	Specificity	-0.126	0.005	-25.19	<.0001
	Analytic	0.023	0.006	3.76	0.0002
	Authentic	0.001	0.000	16.83	<.0001
LIWC Emotion and Drive	Pos Emotion	0.000	0.000	-4.56	<.0001
	Neg Emotion	0.004	0.000	11.07	<.0001
	Achievement	0.002	0.000	6.34	<.0001
	Power	0.022	0.001	37.92	<.0001
	Reward	0.003	0.000	8.99	<.0001
Topic	Policy Topic	0.013	0.001	21.12	<.0001
	Cont. Exchange	0.086	0.007	12.22	<.0001
	Abstract Theme	0.192	0.006	31.33	<.0001
	Appearance	0.175	0.013	13.04	<.0001
Controls	Trump	0.033	0.004	8.49	<.0001
	Aug Debate	-0.097	0.005	-20.52	<.0001
	Feb Debate	-0.102	0.007	-15.03	<.0001
	March Debate	-0.055	0.006	-8.84	<.0001
Model	Intercept	-1.893	0.008	-233.74	<.0001
	Dispersion	0.596	0.002	338.26	<.0001