Supplementary Materials

A Bad Workman Blames his Tweets: The Consequences of Citizens' Uncivil Twitter Use when Interacting with Party Candidates

Supplementary Material A: *Extended overview of the literature on the effects of incivility on political discussions*

Racist, homophobic, shaming or ridiculing remarks are hardly inspiring conversation starters and, as research has shown, may have strong negative consequences even for those simply observing an online discussion (Anderson, Brossard, Scheufele, Xenos, & Ladwig, 2013; Gervais, 2015; Lyons & Veenstra, 2016). Indeed, individuals respond negatively to incivility directed at them or their views, and it may even influence the formation of negative attitudes about the issue at hand (Hwang, Borah, Namkoong, & Veenstra, 2008). Moreover, incivility in online exchanges makes participants perceive uncivil statements as less fair, informative and credible (Brooks & Geer, 2007; Ng & Detenberg, 2005) (but see the study by Thorson et al (2010) who, however, operationalize incivility as derogatory comments). More broadly, and importantly from a democratic point of view, previous research has found that impolite, and especially uncivil, discourse can have a widespread poisonous and polarising effect on discussions (Anderson et al., 2013; Lyons & Veenstra, 2016), even to those simply reading, but not participating, in online conversations (known also as "lurkers"), thus providing a disincentive for engaging in dialogue. This is further corroborated in studies showing that exposure to uncivil political talk induces feelings of anger and aversion, which in turn reduces satisfaction with the message board discourse (Gervais, 2015). Similarly, Lyons and Veenstra (2016, p.14) found that, if a politician's message on Twitter is viewed unsympathetically, and presumably commented upon in an uncivil manner so as to reflect this, the entire discussion surrounding it might collapse.

We believe that these effects may be visible on discussions with politicians, a topic which to our knowledge has not been investigated before. Existing research on journalists' involvement in comment sections on Facebook has shown that engagement from reporters in discussions turned uncivil tends to sooth uncivil discussion, leading to less incivility. Yet, we argue that due to the anonymous nature of Twitter (as opposed to the largely eponymous nature of Facebook), the more complex and subtle way in which discussions by multiple people appear on Twitter (as opposed to the structured discussion threads on Facebook) and, crucially, the largely disliked, distrusted and even despised, personae of politicians (as opposed to the mostly credible journalists), means that engagement from them will tend to induce, rather than soothe, impoliteness and incivility[1].

Given this line of thinking politicians' and strategists' decisions may not be as straightforward when it comes to adopting an engaging style on Twitter. As Stromer-Galley notes in her work on controlled interactivity, giving up some communication control in order to benefit from the affordances of social media involves trade-offs, and in this case the trade-off is engaging with the risk of being trolled. Given the clear benefits of directly addressing people on Twitter, however, some candidates may be willing to take that risk to engage the public. Furthermore, it is plausible that structural constraints apply too and that, for example, candidates in countries where political elites and institutions enjoy high levels of citizen trust may be less likely to be harassed online and thus more comfortable in frequently engaging the public. Previous research has shown that there is variation among incumbents and challengers when it comes to Twitter adoption and frequency of using the platform, while studies have also identified a geographical divide between active Northern European politicians and less active Southern European (Vergeer & Hermans, 2013, p. 142). Other studies have shown that candidates lagging behind in the polls are more likely to experiment in involving the public and supporters online than candidates leading the polls (Stromer-Galley, 2014, p. 34).

[1] We note here that given the generalised impact of incivility on political discussions, in this study we perceive uncivil conduct as a broadly poisonous attitude - not only as something which has negative effects on those towards whom is directed.

Supplementary Material B: *Country specific Twitter presence statistics*

For each specific country, we report the total number of MEP candidates for large or special parties (generally small, but EP election relevant parties in terms of pronounced pro- or anti-EU issue focus), with remaining numbers collapsed into "Other". Depending on the country, the data collection started with checking whether candidates had a social media profile, but for small/fringe parties only select candidates were checked. If a candidate was not checked for a Twitter account, we treat it here as "not having an account". Top of the list refers to the first 33% on the electoral lists (for each party), Middle of the list is 33-66% in terms of position, and Bottom of the list is last 33% of each list (above 66^{th} percentile).

The average percentage of MEP candidates with a presence on Twitter is 16% across all 28 EU countries. This proportion is much lower than the one reported by Lorenzo-Rodriguez and Madariaga (2015): 42.69% of MEP candidates had Twitter accounts. However, their dataset included only candidates running in parties with existing representation in the European Parliament, which excludes new parties such as Podemos in Spain. Their analysis shows that candidates who make an active use of this platform are incumbents and members of large national parties, although gender does not correlate with Twitter presence and use. As detailed in the supplementary material C when restricting our data using similar filters, our MEP candidate Twitter presence is in line with those reported previously in the literature. For example, 40% of the MEP candidates from the German SDP had a Twitter presence, or 87 % of the British Labour candidates for comparison. Furthermore, we also find that those higher up on the party electoral lists are more likely to have an active Twitter presence. Hence, the lower Twitter presence averages reflect the plethora of parties and candidates (almost all) covered by our data collection rather than any systematic difference. That said, even if there was some systematic difference, this is not a problem for our analysis, since here we are only interested in the population of candidates with a Twitter account, but our results may vary in the future as more candidates start adopting this platform.

Germany:

946 total candidates, 723 candidates checked, 173 candidates on Twitter (12 inactive/private profiles, 48 identified only at later stage), and 25 different parties/lists
Detailed statistics for parties (8 parties above 2% of the party list vote in the 2013 Federal elections, 5 in the Bundestag)

Party	N (total)	% on Twitter			
		All	Top of list	Middle of list	Bottom of list
1. CDU/CSU	206	23	42	19	12
2. SPD	96	40	69	27	18
3. FDP	102	31	45	31	14
4. Grune	26	73	100	67	50
5. Die Linke	20	45	71	14	50
6. Piraten	12	92	100	100	75
7. AfD	28	21	40	10	12
8. Other	456	2			

Note: For the remaining parties we only checked if the top 15 candidates on the list had a Twitter account. It is worth mentioning that with the exception of the Free Voters, which had a vote share of 1.5%, all the aforementioned parties got less than 1% of the total votes and their total vote share sums to 7.4%.

Greece:

544 total candidates, 121 candidates on Twitter (22 identified only at later stage), and 14 different parties/lists

Detailed statistics for parties (8 parties)

Party	N (total)	% on Twitter			
		All	Top of list	Middle of list	Bottom of list
1. CRL	40	52	54	54	50
2. ND	42	57	43	50	79
3. Elia	41	56	50	62	57
4. ToPot	42	26	21	36	21
5. IG	42	26	29	29	21
6. GEC	32	12	20	9	9
7. G	42	19	36	7	14
8. DL	40	30	23	15	50
9. Other	223	3			

Spain:

2105 total candidates, 648 checked candidates, 404 candidates on Twitter (4 inactive/private profiles, 25 identified only at later stage), and 39 different parties/lists

Detailed statistics for parties (11 parties)

Party	N	% on Twitter			
		All	Top of list	Middle of list	Bottom of list
1. CS	54	50	100	53	0
2. PP	54	76	100	84	44
3. Vox	54	18	59	0	0
4. EPDD	54	48	94	53	0
5. CEU	54	50	100	53	0
6. LPD	54	57	100	63	11
7. PE	54	72	100	74	44
8. PSOE/PSC	54	100	100	100	100
9. UPyD	54	100	100	100	100
10. PODEMOS	54	70	100	74	39
11. IP	54	100	100	100	100
12. Other	1511	0.2			

Note: We did not check if the candidates of the other 27 parties and lists had Twitter accounts. It is worth mentioning that none of the 27 parties received more than 1% of the vote and their total vote share sums to 8%.

UK:

751 total candidates, 568 candidates checked, 360 candidates on Twitter (18 inactive/private profiles, 46 identified only at later stage), and 46 different parties/lists

Detailed statistics for parties (7 main parties)

Party	N (total)	% on Twitter			
		All	Top of list	Middle of list	Bottom of list
1. Labour	70	87	95	89	76
2. Conservatives	71	72	77	75	62
3. Liberal Democrats	70	93	100	89	90
4. Plaid Cymru	4	100	100	100	100
5. UKIP	70	74	86	78	57
6. SNP	6	100	100	100	100
7. BNP	70	11	32	4	0
8. NI parties	9	89			
9. Other	381	28			

Note: For 28 parties and lists we only checked if the top 3 candidates in each constituency had a Twitter. All these parties received less than 1.1% of the vote and their total vote share sums to 5.1%

Supplementary Material C: *Summary of coding, machine learning classification, and variable statistics*

After compiling the codebook, the coding process proceeded as follows. First, we recruited six coders that would each code 7000 tweets. Our goal was to have around 7000 tweets coded in the main language of each of the four countries –3,500 tweets by the candidates and 3,500 tweets mentioning the candidate, in order to have a balanced sample. Of these 7,000, approximately half of the tweets were coded by two coders so that we can assess inter-coder reliability. As described below, due to duplicate Tweets, language discrepancy, and empty or spam Tweets containing no relevant text (only handles for example), the final number of Tweets coded was lower, but reflects roughly equal amount of candidate vs public Tweets, with half of them coded by two coders.

The coding process started with a training session in which the coders were introduced to the coding scheme, the software used for coding (i.e. CrowdFlower) and went through a number of short exercises (coding around 40 English language tweets). After the training session all coders were assigned the same 160 English language tweets as a follow-up exercise. This was used to evaluate the overall reliability across all six coders, offer feedback to the coders, and for minor adjustment of the codebook. Given that for the coding of the respective tweets the average reliability was satisfactory across all categories, we went further with assigning the country-specific tweets. As a first step the coders were asked to analyse 1000 tweets. After this stage was finalized, the reliability across all countries was re-assessed and in the cases where the reliability indicators were not satisfactory the coders received detailed feedback. At this point we also introduced the language sub-category to the filter question as we noted that in the case of Spain there were a number of tweets in Catalan and Basque, and also in the case of Germany the presence of two least leading candidates among the EP candidates (i.e. Martin Schulz for the Social Democrats groups and Ska Keller for the Greens) meant that a large proportion of the tweets addressed to them were not in German. Following this clarification, the coders received the last batch of 6000 Tweets in early April. This was subsequently supplemented with 2000 tweets for Germany and 1000 tweets for Spain in order to compensate for the language issue mentioned above.

Table C1: Inter-coder reliability statistics

		Germany	Greece	Spain	UK
Summary	Coded by 1/ by 2	2947/2819	2787/2955	3490/1952	3189/3296
	Total coded	5766	5742	5442	6485
Communication	Broadcasting	2755	2883	1771	1557
	Engaging	3011	2859	3671	4928
% Agreement/Krippendorf/Maxwell		79/0.58/0.59	85/0.70/0.70	84/0.66/0.69	85/0.62/0.70
Tone	Impolite	399	1050	121	328
	Polite	5367	4692	5321	6157
% Agreement/Krippendorf/Maxwell		92/0.30/0.85	80/0.26/0.60	93/0.17/0.87	95/0.54/0.90
Morality	Moral	265	204	437	531
	Other	5501	5538	5005	5954
% Agreement/Krippendorf/Maxwell		95/0.50/0.91	97/0.53/0.93	96/0.41/0.92	90/0.39/0.81

Notes: the total number of valid tweets is less than 7,000 because here we exclude tweets we classified as "spam" or in other languages. As measures of inter-coder reliability, we report the percent agreement between the coders for those tweets coded by two coders, Krippendorff's alpha, and also Maxwell score as we consider it most appropriate measure of ICR because it is specifically designed for dichotomous variables.

The machine learning classification task consisted on the following steps. First, we processed the text of the labeled tweets by removing stopwords in each of the four languages, converting to lowercase, transliterating all characters to ASCII (e.g. replaced *á* by *a*) to avoid problems with accentuation differences, stemming all the words to convert them into tokens, and splitting the text into unigrams (tokens) and bigrams (sets of two tokens). We kept all hashtags as they were published, but we substituted all Twitter handles by just an @ sign to avoid overfitting.[1] To further remove extremely rare and extremely frequent n-grams, which are likely to add noise to our classifier, we only consider n-grams that appear in two or more tweets, and in less than 90% of all tweets.

The second step in our analysis is to estimate the parameters of our classifiers. In particular, we use a regularized logistic regression with L2 penalty (ridge regression) that regresses a binary variable indicating whether the tweet corresponds to one or another category on a vector of n-gram counts that indicates the number of times each of the n-

[1] Since we are aggregating tweets at the candidate level, if tweets mentioning the name of a particular candidate are more likely to contain impolite content, then his or her name would be a good predictor of impoliteness, which would induce bias in our analysis.

grams we consider is mentioned in that tweet.[2] We use regularization in order to deal with the sparseness in our feature matrix (each tweet only contains a few words, and the rest of word counts is zero) and because we have more variables than observations in our dataset. Since tweets in our dataset are written in different languages, we run a different model for each country and variable. We estimated these machine learning classifiers using the python library *scikit-learn* (Pedregosa et al, 2011).

In Table C2 we report different measures of performance for our classifiers in each country. To compute these measures, we use 5-fold cross-validation: we split each dataset randomly into 5 sets ("folds") with 20% of the observations each; we train the classifier with the remaining 80% of the data, predict the labels for the remaining 20%, and compare with their true values; this procedure is repeated 5 times, each time using a different 20% "fold."

Table C2: Classifier performance

		UK	Spain	Greece	Germany
Communication Style	Accuracy	0.821	0.775	0.863	0.806
	Precision	0.837	0.795	0.838	0.818
	Recall	0.946	0.890	0.894	0.832
	Baseline	0.752	0.662	0.509	0.549
Polite vs. impolite	Accuracy	0.954	0.976	0.821	0.935
	Precision	0.955	0.977	0.849	0.938
	Recall	0.998	1.000	0.953	0.997
	Baseline	0.949	0.976	0.825	0.937
Morality	Accuracy	0.895	0.913	0.957	0.922
	Precision	0.734	0.665	0.851	0.770
	Recall	0.206	0.166	0.080	0.061
	Baseline	0.879	0.906	0.954	0.919

Notes: *accuracy* is the % of tweets correctly classifier; *precision* is the % of tweets with predicted value of 1 (engaging; polite; related to morality) correctly classified; *recall* is the % of tweets with predicted value of 0 (broadcasting; impolite; not related to morality) correctly

[2] Note that in the classifier we exclude tweets marked as spam by our coders.

classified; *baseline* is the proportion of tweets in the modal category for each variable (engaging; polite; not related to morality)

To ensure that the predicted values we are estimating correspond to our constructs of interest, we also extracted the top predictive n-grams for each category, that is, the n-grams that correspond to the variables with the highest and lowest coefficients in the regularized logistic regression. In Table C3 we report the top 25 n-grams for the three categories of interest in the UK, to illustrate our results.

Table C3: Top predictive stemmed n-grams for classifiers

	Communication style
Broadcasting	just, hack, #votegreen2014, :, and, @ ’, tonight, candid, up, tonbridg, vote @, im @, follow ukip, ukip @, #telleurop, angri, #ep2014, password, stori, #vote2014, team, #labourdoorstep, crimin, bbc news
Engaging	@ thank, @ ye, you’r, @ it’, @ mani, @ pleas, u, @ hi, @ congratul, :), index, vote # skip, @ good, fear, cheer, haven’t, lol, @ i’v, you’v, @ that’, choice, @ wa, @ who, @ hope
	Politeness
Impolite	cunt, fuck, twat, stupid, shit, dick, tit, wanker, scumbag, moron, cock, foot, racist, fascist, sicken, fart, @ fuck, ars, suck, nigga, nigga ?, smug, idiot, @arsehol, arsehol
Polite	@ thank, eu, #ep2014, thank, know, candid, veri, politician, today, way, differ, europ, democraci, interview, time, tonight, @ think, news, european, sorri, con- gratul, good, :, democrat, seat
	Morality and democracy
Others	@ ha, 2, snp, nice, tell, eu, congratul, campaign, leav, alreadi, wonder, vote @, ;), hust, nh, brit, tori, deliv, bad, immigr, #ukip, live, count, got, roma
Moral/Dem.	democraci, polic, freedom, media, racist, gay, peac, fraud, discrimin, homosexu, muslim, equal, right, crime, law, violenc, constitut, faith, bbc, christian, marriag, god, cp, racism, sexist

Summary statistics: Germany

Variable	Mean	Std. Dev.	Min.	Max.	N
% engaging tweets sent	0.26	0.17	0.01	0.92	92
% impolite tweets received	0.06	0.03	0	0.2	90
% tweets about morality/democ.	0.09	0.1	0.01	0.88	90
Incumbent candidate (dummy)	0.3	0.46	0	1	117
Electability: doubtful	0.09	0.29	0	1	117
Electability: safe	0.3	0.46	0	1	117
Electability: unpromising	0.61	0.49	0	1	117
Candidate is male (dummy)	0.67	0.47	0	1	117
Tweets sent by candidate	114.75	205.19	0	979	117
Tweets received by candidate	576.58	3228.09	0	33452	117
Number of followers	3386.46	15456.86	1	155193	104
Ideology of candidate	4.77	1.27	-0.03	6.26	66
EU position of candidate	6.48	0.84	4.48	7.45	66
National vote share	15.23	12.29	1	34.1	117
National incumbent party (dummy)	0.41	0.49	0	1	117

Summary statistics: Spain

Variable	Mean	Std. Dev.	Min.	Max.	N
% engaging tweets sent	0.45	0.11	0.22	0.84	212
% impolite tweets received	0.04	0.04	0	0.28	211
% tweets about morality/democ.	0.1	0.06	0	0.43	211
Incumbent candidate (dummy)	0.07	0.26	0	1	225
Electability: doubtful	0.15	0.36	0	1	225
Electability: safe	0.1	0.3	0	1	225
Electability: unpromising	0.75	0.43	0	1	225
Candidate is male (dummy)	0.6	0.49	0	1	225
Tweets sent by candidate	269.55	385.45	0	2647	225
Tweets received by candidate	1717.86	8339.83	0	99294	225
Number of followers	8452.71	61523.6	10	866563	205
Ideology of candidate	4.57	1.19	1.6	6.52	175
EU position of candidate	6.01	0.24	5.46	6.41	175
National vote share	8.4	11.84	0	41.9	225
National incumbent party (dummy)	0.05	0.22	0	1	225

Summary statistics: Greece

Variable	Mean	Std. Dev.	Min.	Max.	N
% engaging tweets sent	0.19	0.11	0.03	0.58	79
% impolite tweets received	0.18	0.11	0	0.52	70
% tweets about morality/democ.	0.04	0.04	0	0.28	70
Incumbent candidate (dummy)	0.08	0.27	0	1	99
Electability: doubtful	0.02	0.14	0	1	99
Electability: safe	0.07	0.26	0	1	99
Electability: unpromising	0.91	0.29	0	1	99
Candidate is male (dummy)	0.66	0.48	0	1	99
Tweets sent by candidate	58.62	110.8	0	839	99
Tweets received by candidate	93.44	260.77	0	1692	99
Number of followers	2056.33	4797.74	3	37314	90
Ideology of candidate	4.63	1.91	-0.29	6.9	53
EU position of candidate	6.66	0.05	6.49	6.74	53
National vote share	15.18	11.04	0	29.7	99
National incumbent party (dummy)	0.4	0.49	0	1	99

Summary statistics: UK

Variable	Mean	Std. Dev.	Min.	Max.	N
% engaging tweets sent	0.53	0.14	0.04	0.92	271
% impolite tweets received	0.05	0.03	0	0.2	266
% tweets about morality/democ.	0.06	0.04	0	0.25	266
Incumbent candidate (dummy)	0.16	0.37	0	1	303
Electability: doubtful	0.04	0.2	0	1	304
Electability: safe	0.12	0.32	0	1	304
Electability: unpromising	0.84	0.37	0	1	304
Candidate is male (dummy)					0
Tweets sent by candidate	169.42	330.06	0	3720	304
Tweets received by candidate	656.84	3077.93	0	48781	304
Number of followers	3119.31	13093.55	0	191616	264
Ideology of candidate	5.19	1.04	4.24	8.18	176
EU position of candidate	5.18	0.58	3.75	6.14	176
National vote share	15.61	14.33	0	36.1	304
National incumbent party (dummy)	0.32	0.47	0	1	304

Supplementary Material D: *Coding instructions*

Social Media and 2014 EU Election Project

In this job, you will be presented with tweets about the 2014 European elections. You will need to classify each tweet into the following series of categories:

1. Polite Vs. Impolite

- **Polite** (a tweet that adheres to politeness standards, i.e. it is written in a well-mannered and non-offensive way) – *@paulmasonews why doesnt #EU take a longer term view? Doesnt #Germany remember their 1940s bailout allowing recovery & growth? #Greece*

- **Impolite** (an ill-mannered, disrespectful tweet that may contains offensive language. This includes: threatening one's rights (freedom to speak, life preferences), assigning stereotypes or hate speech ("nigger", "faggot"), name-calling ("weirdo", "traitor", "idiot"), aspersion ("liar", "traitor"), pejorative speak or vulgarity, sarcasm, ALL CAPS, incendiary, obscene, humiliating.

  – *@Nigel_Farage How's your dirty European non British dirty bitch of a wife? Is she ok? Can't imagine what it's like for you.*

  – *@SLATUKIP – "@DavidCoburnUKip Oh shut up David. You're a bore. @marley68xx"*

2. Communication Style

- **Broadcasting** (a statement or an expression of opinion)

  – *@PaulBrannenNE – "Labour's freepost election address dropping through letter boxes across the North East this week."*

- **Engaging: directed to someone else/another user** (a direct response)

  – *@GreenJeanMEP – "@klebudd Thank you Katie. We aimed for a positive campaign #Vote- Green2014"*

3. Political content (other categories omitted)

• **Morality and democracy** (tweets that make reference to one of the following topics: freedom and human right, traditional morality, law and order, social harmony, freedom and human rights, democracy, constitutionalism)

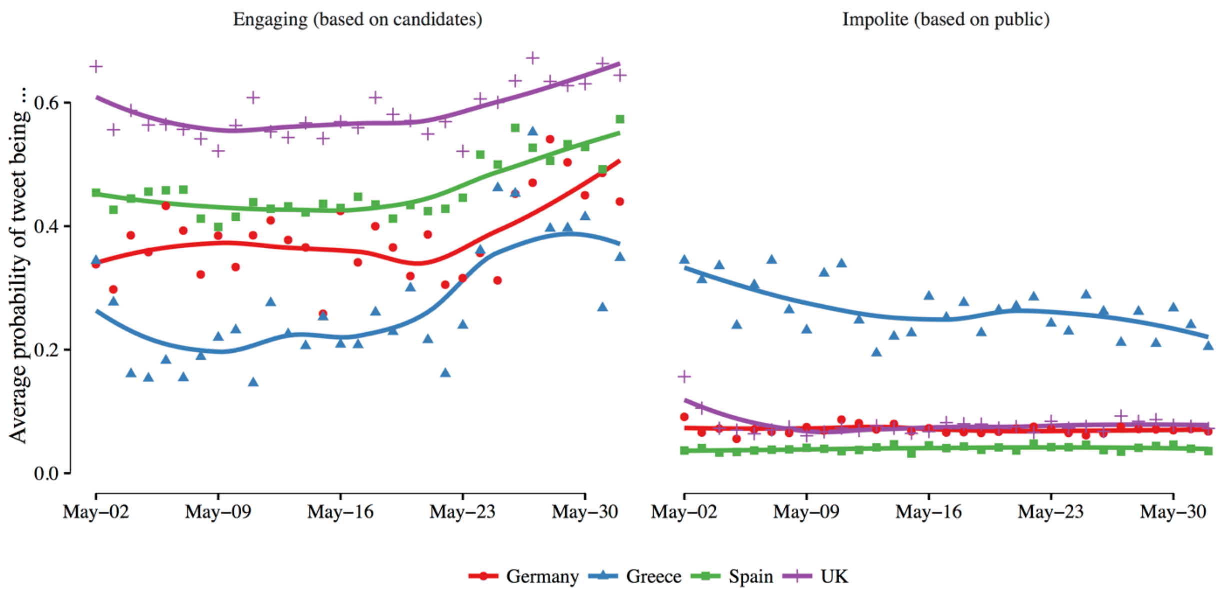
– *@NATOWales but what about the defense of democracy and freedom of speech???*

– *@Magee__ That was dropped. He was then arrested for the content of the speech.*

Supplementary Material E: *Additional Results*

The following Figure complements the analysis in the Results section of the paper by demonstrating that the differences we identified across countries are stable over time. The left panel displays the average probability that the tweets sent by candidates in each country and day are classified as engaging. The less smooth line overlaid on top reveals a monotonic increase in candidates' outreach to voters through social media as the campaign progresses, and in particular after the election day, in many cases to thank voters for their support. On the contrary, the proportion of impolite tweets received by candidates during the campaign remained relatively stable during this period, as we show in the right panel. The only exception to this general pattern is Greece, where we see a gradual decline during the campaign.

Figure E1: Average proportion of engaging tweets sent and impolite tweets received, by day and country



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