Political Knowledge and Misinformation in the Era of Social Media: Evidence from the 2015 U.K. Election
Online Appendix

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March 17, 2020

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Appendix A: Details about Tweet Classification Process and Tweet Examples

As noted in the text, we selected four topics that we determined were likely to be highly salient in the election – the economy; the U.K.'s ties to the European Union (EU); immigration; and the fight against the ISIS terrorist organization – and identified tweets relevant to these topics. We identified all tweets on users' timelines related to these topics by first manually constructing short lists of terms related to each topic. We then identified which other terms most frequently co-occurred in tweets with the original anchor terms. We then used these expanded lists of terms to create our final lists of tweets related to each of the four topics.

For example, we began the process of identifying tweets related to the topic of ties to the EU by finding all tweets that included the anchor terms "Brexit" or "Euro-skeptic." We purposefully began with this short, idiosyncratic and incomplete list in order to substantially reduce the chance of false positives. Incorporating all tweets with these anchor terms into the subset s, we then calculated a score reflecting the relative frequency with which any word w was found in s, weighted by how prominent w was in Twitter discussions about the topic:

$$Score_s^w = \frac{f_s^w N_s^w}{f^w},$$

where f_s^w is the share of tweets in s including the word w, f^w is the share of tweets in our entire corpus of tweets containing word w, and N_s^w is the number of times word w appeared in subset s.

The following are the terms used to create each of the topics analyzed in the paper. If a tweet contained terms from multiple topics, it was labeled as belonging to each of those topics.

In implementing the keyword generation and topic-tweet matching procedure described in the body of the paper, we elected to use exact token matching and avoid any pre-processing. Some of the keywords generated (eg "no2eu") were irregular words or contained numbers, and pre-processing steps like stemming might have introduced unexpected errors. The downside to this decision is primarily in the way that variations on certain terms are included or excluded in the list of keywords: note that both "cuts" and "cut" (also "benefit" and "benefits"; "reforms" and "reform") appear in the list of keywords for the Economy topic, meaning that it is slightly narrower than if we had included a single "cut[s]" token as well as the next-most-likely token. On balance, we think that this decision is defensible and that the decreased risk of error outweighs this drawback.

Sample Economy tweets:

- Labour (@EdMilliband): "Tomorrow, I'm asking you to vote to rescue our NHS, to build a future for all our young people and to reward hard work."
- Right Media (@TheSun): "The Budget2015 shows voters have a choice between facts and scary fairy tales: [link] SunNation."

Sample ISIS tweets:

- UKIP (@NigelFarage): "Given the clear Isis threat, idea EU open borders somehow makes us safer is crackers. UK would be far safer outside of EU."
- Left Media (@Guardian): "Islamic State extremists bulldoze ancient Nimrud site near Mosul [embedded link]."

Sample Immigration tweets:

- UKIP (@UKIP): "UKIP understands that with our public services under increasing strain we have to draw a line under the past 11 years of mass immigration"
- Left Media (@Independent): "Why are there less kids playing football in the street? Because of immigration, says Ukip [embedded link]."

Sample Ties to the EU tweets:

- Conservatives (@Conservatives): "WATCH AND SHARE: Cameron - only the Conservatives will give you an EU referendum leadersdebate [embedded video]"
- Center Media (@FT): 'A British exit from the EU is possible under virtually any election outcome: [embedded link] GE2015."

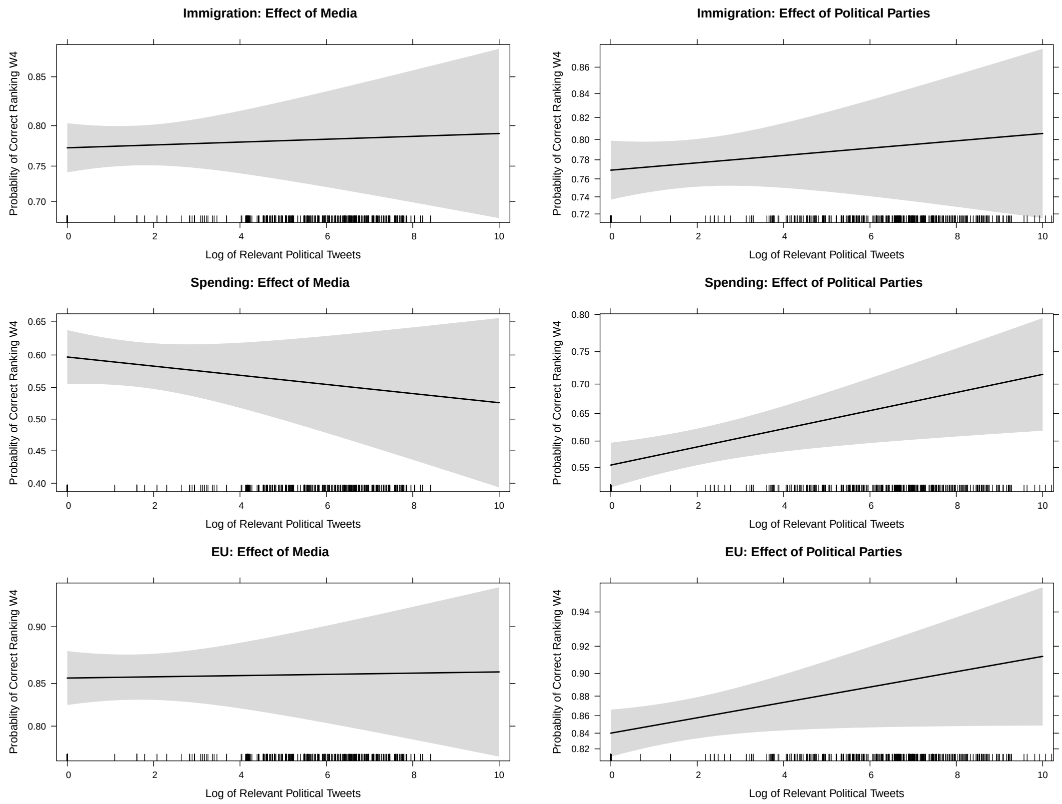
We provide some illustrative examples of tweets that demonstrate the plausibility of the causal pathway proposed in our analysis. These are tweets 1) sent by accounts that are followed by respondents in our sample between Wave 2 and Wave 3 of our panel survey; 2) containing a keyword that lead our classification procedure to categorized them as a topic in our analysis; and 3) containing information that could plausibly cause the changes in knowledge we document in the article.

Figure 1 displays two such tweets. The first tweet, from UKIP, clearly contains information that could cause a reader to change their estimate of the true rate of immigration into the UK in an upward direction.

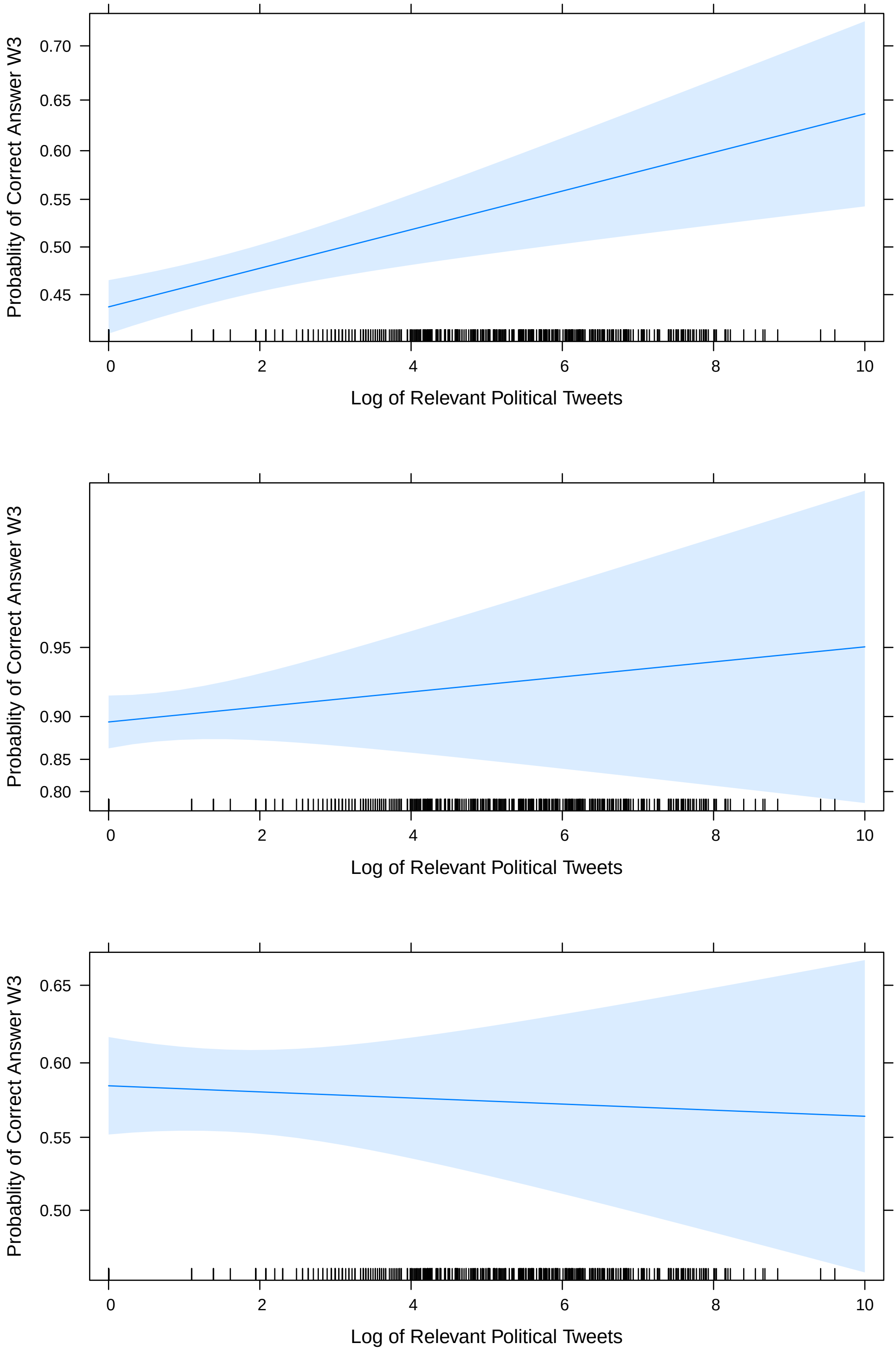
The second tweet, sent by Labour, demonstrates our more surprising result about knowledge of the economy. Recall that the true state of the economy was such that unemployment fell under the Conservative/Liberal Democrat government. Labour, as an opposition party, faced a clear incentive to obscure this fact; this tweet illustrates how the party did this by priming negative aspects of the government's economic performance. While containing only true information (many of the claims are subjective, but none are fabricated), the tweet could plausibly lead those exposed to it to be less likely to correctly identify that unemployment had decreased under the incumbent government.

Figure 1: Illustrative Tweets

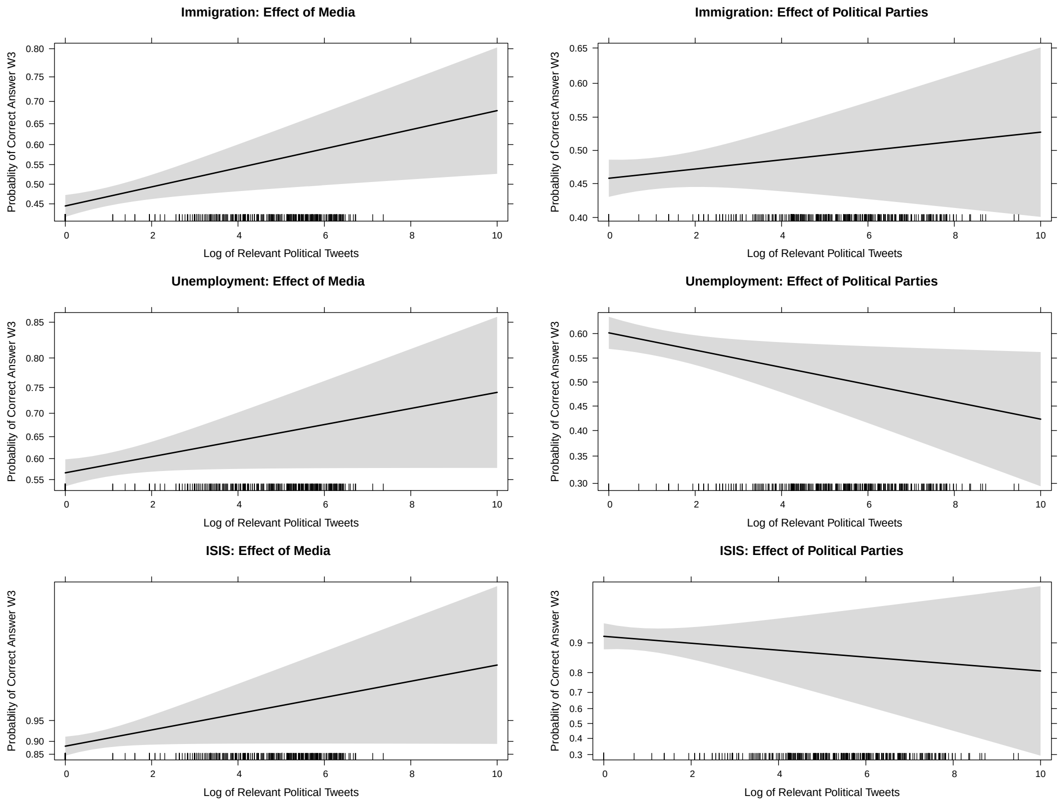
Appendix B: Effects Plots



These plots use the same analysis as those in Figure **??**. Effects plot of the impact of the number of tweets in the respondent's timeline related to the that topic by parties or the media on the probability that they correctly ranked the four parties on that topic in wave 4 of the survey. This assumes that all other variables, including demographic and media consumption control variables, are fixed at their means.



These plots use the same analysis as those in Figure ??. Effects plot of the impact of the number of tweets in the respondent's timeline related to the that topic on the probability that they correctly answered the issue-relevant factual question on that topic in wave 3 of the survey. This assumes that all other variables, including demographic and media consumption control variables, are fixed at their means.



These plots use the same analysis as those in Figure 6. Effects plot of the impact of the number of tweets in the respondent's timeline related to the that topic by parties or the media on the probability that they correctly answered the issue-relevant factual question on that topic in wave 3 of the survey. This assumes that all other variables, including demographic and media consumption control variables, are fixed at their means.

Appendix C: Full Regression Tables

Table 1: Regression Results from Figure **??**

	Dependent variable:		
	EU	Spending	Immigration
Answer Previous Wave	1.751***	1.060***	1.596***
	(0.158)	(0.134)	(0.140)
Topical Tweets Received	0.059**	0.047**	0.036
	(0.028)	(0.021)	(0.024)
Twitter Use Frequency	0.0004	−0.001	0.001
	(0.002)	(0.002)	(0.002)
Woman	0.023	−0.044	−0.317**
	(0.148)	(0.141)	(0.143)
Age	0.005	0.008	0.005
	(0.006)	(0.006)	(0.006)
Lower Class	−0.065	−0.143**	−0.058
	(0.055)	(0.055)	(0.055)
Years Education	0.139**	0.179***	0.183***
	(0.057)	(0.054)	(0.056)
Race: Whtie British	0.246	0.416*	0.213
	(0.236)	(0.222)	(0.232)
Married	0.096	−0.291**	−0.095
	(0.147)	(0.139)	(0.144)
Frequency Watch Newsnight	0.005	−0.007	−0.040
	(0.091)	(0.084)	(0.087)
Religious	−0.135	0.237*	0.167
	(0.146)	(0.141)	(0.143)
Frequency internet Use	0.162	0.191	0.138
	(0.197)	(0.216)	(0.203)
Read Blue Top	−0.309	−0.066	−0.118
	(0.250)	(0.242)	(0.251)
Read Red Top	−0.596**	−0.223	−0.565**
	(0.264)	(0.280)	(0.260)
Read Other Paper	−0.037	0.028	−0.186
	(0.263)	(0.235)	(0.249)
Read No Paper	−0.073	0.188	0.048
	(0.183)	(0.164)	(0.179)
Constant	−1.323	−2.682*	−1.302
	(1.316)	(1.393)	(1.335)
Observations	1,417	1,068	1,376
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Regression Results from Figure **??**

	Dependent variable:		
	ISIS	Unemployment	Immigration
Answer Previous Wave	2.611***	2.274***	0.971***
	(0.215)	(0.116)	(0.099)
Topical Tweets Received	0.090	−0.009	0.076***
	(0.090)	(0.025)	(0.022)
Twitter Use Frequency	0.003	−0.002	−0.001
	(0.003)	(0.002)	(0.001)
Woman	0.020	−0.329***	−0.329***
	(0.210)	(0.118)	(0.101)
Age	0.014	0.010**	0.008*
	(0.009)	(0.005)	(0.004)
Lower Class	−0.065	−0.174***	−0.009
	(0.077)	(0.046)	(0.040)
Years Education	−0.016	0.118**	0.066*
	(0.085)	(0.047)	(0.040)
Race: Whtie British	0.033	0.542***	−0.077
	(0.355)	(0.191)	(0.169)
Married	0.431**	0.074	0.100
	(0.212)	(0.120)	(0.102)
Frequency Watch Newsnight	0.425**	−0.039	−0.091
	(0.168)	(0.074)	(0.062)
Religious	0.006	0.358***	−0.167*
	(0.216)	(0.120)	(0.101)
Frequency internet Use	0.447**	0.419***	0.015
	(0.226)	(0.158)	(0.140)
Read Blue Top	−1.145***	0.739***	−0.258
	(0.434)	(0.215)	(0.171)
Read Red Top	−1.311***	−0.110	−0.289
	(0.446)	(0.227)	(0.199)
Read Other Paper	−0.801*	0.204	−0.003
	(0.483)	(0.215)	(0.181)
Read No Paper	−1.112***	0.128	−0.240*
	(0.356)	(0.148)	(0.126)
Constant	−2.641	−4.119***	−0.564
	(1.650)	(1.062)	(0.934)
Observations	1,892	1,892	1,892
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression Results from Figure **??**

	Dependent variable:		
	EU	Spending	Immigration
Answer Previous Wave	1.749***	1.054***	1.599***
	(0.158)	(0.134)	(0.140)
Topical Media Tweets Received	0.005	−0.029	0.010
	(0.040)	(0.031)	(0.035)
Topical Party Tweets Received	0.069*	0.070***	0.022
	(0.036)	(0.026)	(0.030)
Twitter Use Frequency	0.0005	−0.0002	0.002
	(0.002)	(0.002)	(0.002)
Woman	0.023	−0.041	−0.320**
	(0.148)	(0.141)	(0.143)
Age	0.004	0.008	0.005
	(0.006)	(0.006)	(0.006)
Lower Class	−0.068	−0.146***	−0.058
	(0.055)	(0.056)	(0.055)
Years Education	0.140**	0.183***	0.184***
	(0.057)	(0.055)	(0.056)
Race: Whtie British	0.248	0.434*	0.219
	(0.236)	(0.222)	(0.232)
Married	0.098	−0.286**	−0.095
	(0.147)	(0.139)	(0.144)
Frequency Watch Newsnight	0.010	0.001	−0.036
	(0.091)	(0.084)	(0.088)
Religious	−0.142	0.230	0.168
	(0.146)	(0.141)	(0.143)
Frequency internet Use	0.168	0.198	0.147
	(0.197)	(0.216)	(0.203)
Read Blue Top	−0.318	−0.091	−0.128
	(0.250)	(0.243)	(0.252)
Read Red Top	−0.604**	−0.244	−0.581**
	(0.264)	(0.281)	(0.259)
Read Other Paper	−0.038	0.034	−0.196
	(0.263)	(0.236)	(0.248)
Read No Paper	−0.073	0.182	0.041
	(0.182)	(0.164)	(0.179)
Constant	−1.331	−2.720*	−1.337
	(1.316)	(1.393)	(1.335)
Observations	1,417	1,068	1,376
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression Results from Figure 6

	Dependent variable:		
	ISIS	Unemployment	Immigration
Answer Previous Wave	2.607***	2.281***	0.969***
	(0.216)	(0.117)	(0.099)
Topical Media Tweets Received	0.298**	0.078*	0.092***
	(0.151)	(0.040)	(0.035)
Topical Party Tweets Received	−0.089	−0.072**	0.025
	(0.126)	(0.032)	(0.029)
Twitter Use Frequency	0.003	−0.002	−0.001
	(0.003)	(0.002)	(0.001)
Woman	0.033	−0.326***	−0.323***
	(0.210)	(0.118)	(0.101)
Age	0.015*	0.011**	0.008*
	(0.009)	(0.005)	(0.004)
Lower Class	−0.054	−0.171***	−0.007
	(0.078)	(0.046)	(0.040)
Years Education	−0.016	0.116**	0.066*
	(0.085)	(0.047)	(0.040)
Race: Whtie British	−0.001	0.539***	−0.077
	(0.357)	(0.192)	(0.169)
Married	0.427**	0.068	0.096
	(0.213)	(0.120)	(0.103)
Frequency Watch Newsnight	0.411**	−0.045	−0.098
	(0.167)	(0.074)	(0.063)
Religious	0.007	0.362***	−0.163
	(0.216)	(0.120)	(0.102)
Frequency internet Use	0.459**	0.421***	0.021
	(0.227)	(0.158)	(0.140)
Read Blue Top	−1.132***	0.749***	−0.251
	(0.434)	(0.215)	(0.171)
Read Red Top	−1.296***	−0.114	−0.292
	(0.447)	(0.227)	(0.199)
Read Other Paper	−0.807*	0.199	−0.012
	(0.483)	(0.215)	(0.181)
Read No Paper	−1.108***	0.129	−0.238*
	(0.356)	(0.148)	(0.126)
Constant	−2.747*	−4.142***	−0.597
	(1.659)	(1.062)	(0.935)
Observations	1,892	1,892	1,892
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression Results from Figures 7 and 8

	Dependent variable:	
	Unemployment	Immigration
Answer Previous Wave	2.579***	2.264***
	(0.216)	(0.118)
Topical Labour Tweets Received	−0.010	−0.142***
	(0.151)	(0.036)
Topical UKIP Tweets Received	11.860	0.066
	(455.522)	(0.076)
Topical LibDem Tweets Received	−0.334	−0.035
	(0.284)	(0.064)
Topical Tory Tweets Received	−0.283	0.091*
	(0.275)	(0.054)
Topical Right-Media Tweets Received	0.298	0.084
	(0.578)	(0.094)
Topical Left-Media Tweets Received	0.427	0.091
	(0.567)	(0.088)
Topical Center-Media Tweets Received	0.250	0.071
	(0.163)	(0.044)
Twitter Use Frequency	0.004	−0.003
	(0.003)	(0.002)
Woman	0.054	−0.314***
	(0.211)	(0.119)
Age	0.016*	0.010**
	(0.009)	(0.005)
Lower Class	−0.050	−0.170***
	(0.078)	(0.046)
Years Education	−0.003	0.115**
	(0.085)	(0.047)
Race: White British	−0.012	0.559***
	(0.361)	(0.194)
Married	0.451**	0.061
	(0.213)	(0.121)
Frequency Watch Newsnight	0.409**	−0.037
	(0.168)	(0.074)
Religious	0.001	0.344***
	(0.217)	(0.122)
Frequency Internet Use	0.459**	0.414***
	(0.227)	(0.158)
Read Blue Top	−1.175***	0.701***
	(0.435)	(0.217)
Read Red Top	−1.306***	−0.111
	(0.447)	(0.227)
Read Other Paper	−0.819*	0.198
	(0.484)	(0.217)
Read No Paper	−1.139***	0.105
	(0.358)	(0.149)
Constant	−2.831*	−4.073***
	(1.660)	(1.066)
Observations	1,892	1,892
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix D: Details of Survey Implementation

Respondents received a financial benefit for their participation in the survey. The surveys were conducted online. Each wave lasted approximately 10 minutes, and contained between 50 and 70 questions. We supplemented these surveys responses with demographic information that YouGov asks of all of their respondents.

The retention rates for different waves of the survey can be seen in Table 6. Overall, there were 1308 respondents retained for all 4 waves of the SMU sample, out of the 3,846 who appeared in at least one wave.[1] The retention was lowest between waves 1 and 2, but was otherwise similar to what is often seen in online panel surveys (**?**). Notice that the retention rate is highest between waves 3 and 4. YouGov made an intensive effort to enroll as many previous respondents for the final, post-election wave as possible. Also, wave 4 consists only of respondents who had participated in at least one of the previous three waves, to best take advantage of the panel design.

Table 6: Number of Survey Respondents per Wave

	Wave 1	Wave 2	Wave 3	Wave 4	All Waves
NR respondents	1,118	1,047	1,094	958	1,660
Retention, previous wave		63%	71%	87%	465 (in all 4 waves)
SMU respondents[a]	2,574	2,507	2,776	2,490	3,846
Retention, previous wave[b]		68%	79%	90%	1,308 (in all 4 waves)
New respondents		32%	19%	0%	

[a]Cell entries are the number of respondents in each wave.
[b]Cell entries are the proportion of respondents returning from the previous wave.
Wave 1 concluded on July 31, 2014; wave 2 on December 11; wave 3 on March 30, 2015; and wave 4 (post-election) on June 17.

The four waves of the survey took place over the course of almost a year: wave 1 lasted 22 days and concluded on July 31, 2014; wave 2 lasted 8 days and concluded on December 11, 2014; wave 3 lasted 12 days and concluded on March 30, 2015; and wave 4 lasted 26 days and concluded on June 17, 2015. Wave 4 was in the

[1]In order to maintain the size of the waves, YouGov also replenished the sample, adding respondents in later waves who were not in the first wave.

field for an especially long time as part of the effort to increase the retention rate, and it began 2 weeks after the day of the general election on May 7, 2015.

All told, our sample comprised 5,506 unique subjects, of whom 4,829 completed enough of at least one survey to be included. We have relevant tweets (from at least one of the accounts under study, about one of the relevant topics) from 1,170 subjects, broken down further in Table 2. There are 1,563 respondents who either reported not using Twitter or whose account we verified as following 0 of the relevant political or media accounts. There are 2,096 respondents who reported that they use Twitter but either did not disclose their accounts or disclosed an account that we could not locate; these respondents were excluded from the analysis where tweet counts are explanatory variables.

Table 7: Descriptive Statistics of Twitter Users Who did and did not Share Their Twitter Accounts

Panel A: Covariates

	SMU	SMU (shared tweets)
Women	45%	43%
15+ Years Education	52%	55%
Median Age	48	48
Median HH Income	£34,200	£37,500
Median L-R Ideology†	5.2	5.2

† Self-reported ideology, left to right; asked on a 0-100 scale in our survey and on a 0-10 scale in the BES. The BES is a nationall representative post-election survey of 30,000 voters1.

Panel B: Vote Choice, Post-Election

	SMU	SMU (shared tweets)
Conservative	33	32
Labour	34	35
Liberal Democrats	8	9
SNP	5	5
UKIP	9	8
Green	10	11
Other	1	1
	100%	100%

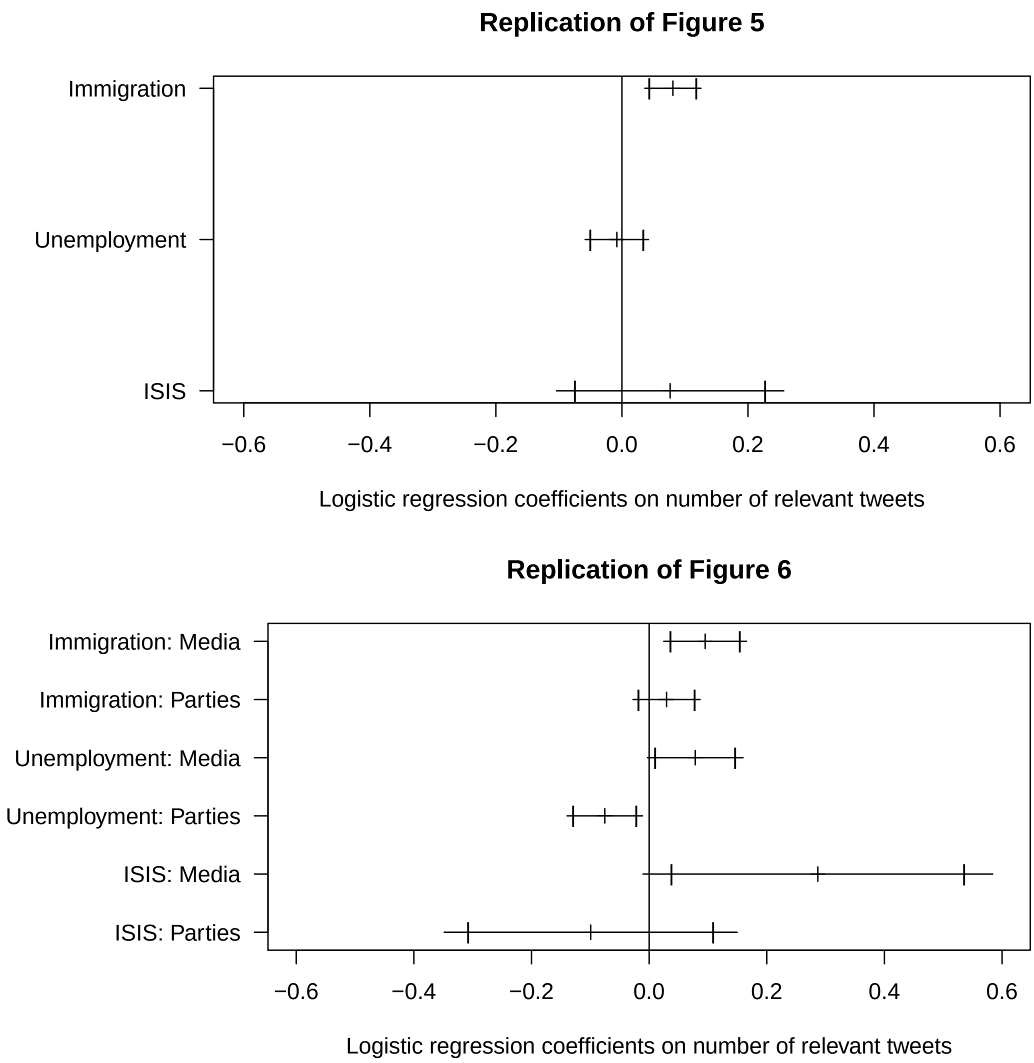
Panel C: UK Country

	SMU	SMU (shared tweets)
England	84	85
Scotland	5	5
Wales	9	9
Northern Ireland	1	1

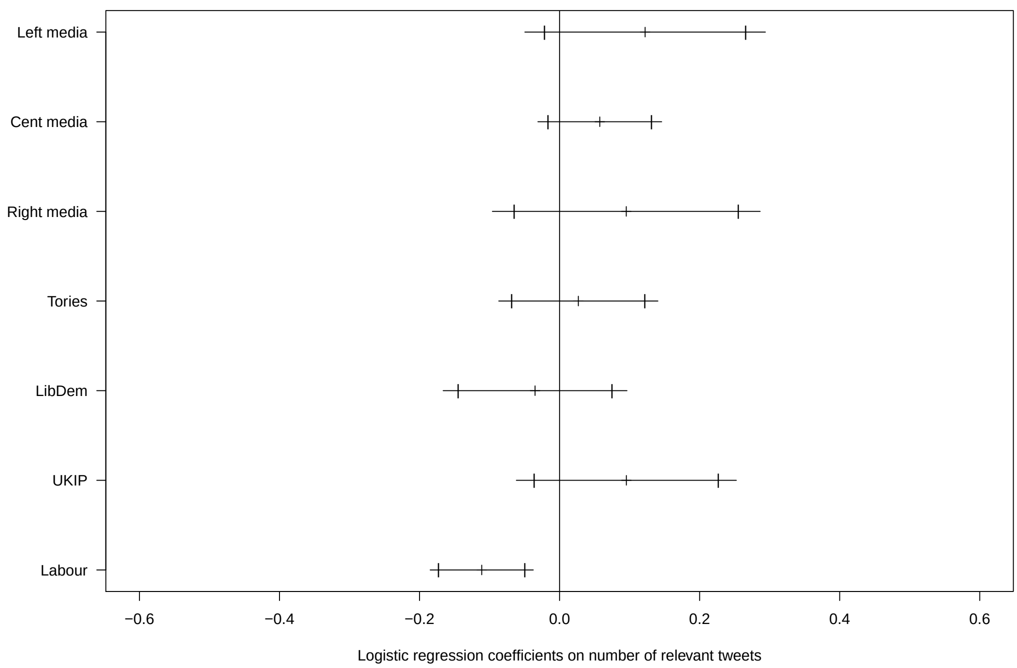
The demographic, vote choice and geographic vote share of the relevant populations: the Social Media Analaysis sample, and the subgroup for whom we have their Twitter timeline.

Appendix E: Effect of Topical Tweets (by Source) on Knowledge of Issue-Relevant Facts Controlling for Party ID

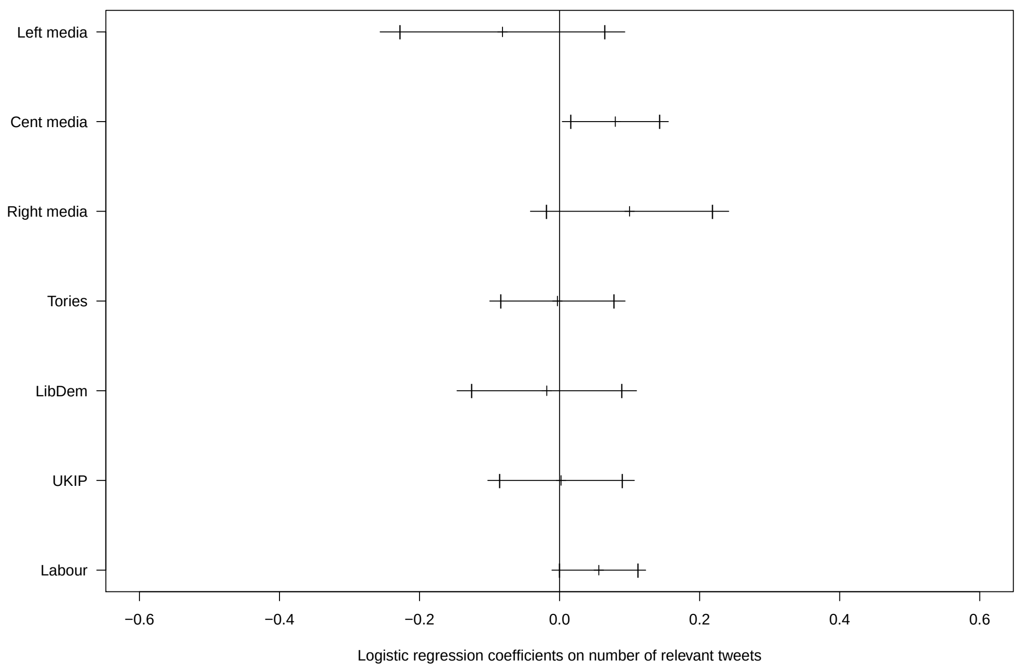
Figure 2: Replicating Figures 5, 6, 7, and 8, Controlling for PID



Replication of Figures 7 and 8:Unemployment



Replication of Figures 7 and 8:Immigration



These plots use the same analysis as those in Figures 5,6, 7 and 8, with added dummy variables for respondents' self-reported party identification. Overall, only the Labour, Conservative and Liberal Democrat parties had significant numbers of partisans among our sample; 26% reported no party affiliation, while only 10% reported that they did not intend to vote. Overall, the addition of these controls does not change any of the statistical inferences presented in the body of the text.

Appendix F: Weighted Regressions Using Raked Demographics From BES

Because our sample was drawn from YouGov's opt-in panel of social media users, there is a potential concern about the generalizability of our results to the population of UK Twitter users. We do have access to the self-reported pool of Twitter users on the British Election Survey. Using the R package "survey" (**?**), we "raked" our data to match the (survey weighted) demographic distribution of BES Twitter users along the dimensions of gender, age, education and household income, then used the resulting survey weights to as a robustness check to the results in the body of the paper.

Figure 3: Weighted Replication of Figure 2: Effect of Topical Tweets on Correctly Identifying Relative Party Placement by Issue

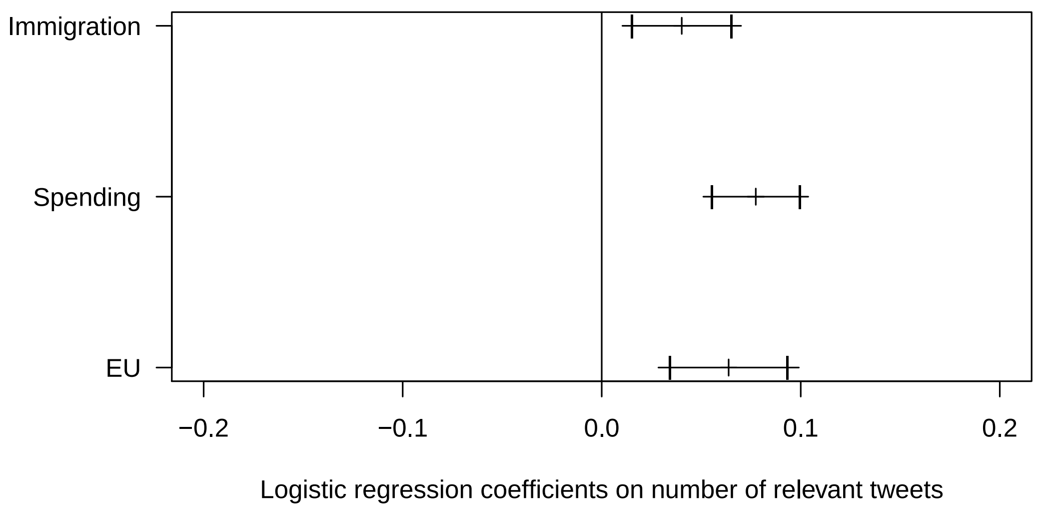


Figure 3 presents the same analysis as in Figure 2 in the body of the text: the overall effect of tweets on a given topic on party placement. The effect on knowledge of immigration is now significant.

Figure 4 presents the same analysis as in Figure 3 in the body of the text; the estimated effects are essentially the same.

Figure 5 presents the same analysis as in Figure 4 in the body of the text: the overall effect of tweets on a given topic on party placement, disaggregated by source. The effect of media tweets on party placement on the topic of immigration is now significant; the rest of the results are largely unchanged.

Figure 7 presents the same analysis as in Figure 6 in the body of the text: the overall effect of tweets on a given topic on factual knowledge, divided by the source of the tweeter (media or politicians). The effects are essentially the same, although better estimated.

Figure 8 presents the same analysis as in Figure 7 in the body of the text: the effect of tweets on factual knowledge of unemployment, divided by the source of the tweeter. Here, the results provide *considerably* stronger evidence for our theory than the results from the unweighted regression in the body of the paper.

Each of the media-ideology clusters effects' is now estimated as positive and significant. But more notably, the effect of tweets from Liberal Democrats goes from slightly negative to *positive and significant*. The latter better fits our theory, as the Liberal Democrats were involved with the coalition government during the election and thus had the same incentive to promulgate knowledge of the low unemployment rate at the time. Furthermore, this result is not cherry-picked: this is the *only* instance where the addition of the survey weights raked from the BES causes a coefficient estimate to switch signs and become statistically significant.

The estimated effect of tweets from the challenger Labour party remains a statistically significant *reduction* in knowledge of the positive economic situation.

Figure 9 presents the same analysis as in Figure 8 in the body of the text: the effect of tweets on factual knowledge of immigration, divided by the source of the tweeter. The effects are essentially the same, although better estimated.

Appendix G: Absolute Knowledge Levels

Table 8: Knowledge of Issue-Relevant Facts

Panel A: Twitter Users (1,469)

	ISIS		Unemployment		Immigration	
	Correct W2	Incorrect W2	Correct W2	Incorrect W2	Correct W2	Incorrect W2
Correct W3	89%	5%	52%	9%	32%	17%
Incorrect W3	2%	3%	14%	25%	20%	30%
Total W2	91%	8%	66%	34%	52%	47%

Panel B: Non-Twitter Users (N=945)

	ISIS		Unemployment		Immigration	
	Correct W2	Incorrect W2	Correct W2	Incorrect W2	Correct W2	Incorrect W2
Correct W3	84%	6%	51%	12%	33%	15%
Incorrect W3	5%	5%	11%	27%	23%	29%
Total W2	89%	11%	62%	39%	56%	44%

Distribution of Responses to Issue Relevant Fact Knowledge Questions: Cell entries are percentages for each possible combination of correct and incorrect answers across wave 2 and wave 3 of the issue-relevant fact questions: (C,C), (C,I), (I,C), (I,I). The bottom row shows how difficult each question was showing the percentage correct in wave 2.

Table 9: Knowledge of Party Placements Among Twitter Users

	EU, N= 1,115	
	Correct W1	Incorrect W1
Correct W4	54%	27%
Incorrect W4	4%	15%
Total W1	58%	42%

	Immigration, N= 1,090	
	Correct W1	Incorrect W1
Correct W4	63%	14%
Incorrect W4	11%	13%
Total W1	74%	27%

	Taxes and Spending, N= 860	
	Correct W1	Incorrect W1
Correct W4	37%	19%
Incorrect W4	16%	28%
Total W1	53%	47%

Cell entries are percentages for each possible combination of correct and incorrect answers across wave 1 and wave 4 of the party placement questions. The bottom row of each panel shows how difficult each question was, giving the percentages correct and incorrect in Wave 1. Note that the large increase in accuracy about party placement in the EU is an artifact of how we coded responses. In Wave 4, the Liberal Democrats and Labour were too close together on this scale, so we coded either ordering of these two parties as correct; in Wave 1, the Liberal Democrats were sufficiently to the left of Labour.

Figure 4: Weighted Replication of Figure 3: Effect of Topical Tweets on Probability of Correctly Identifying Relative Party Placement by Issue in Wave 4

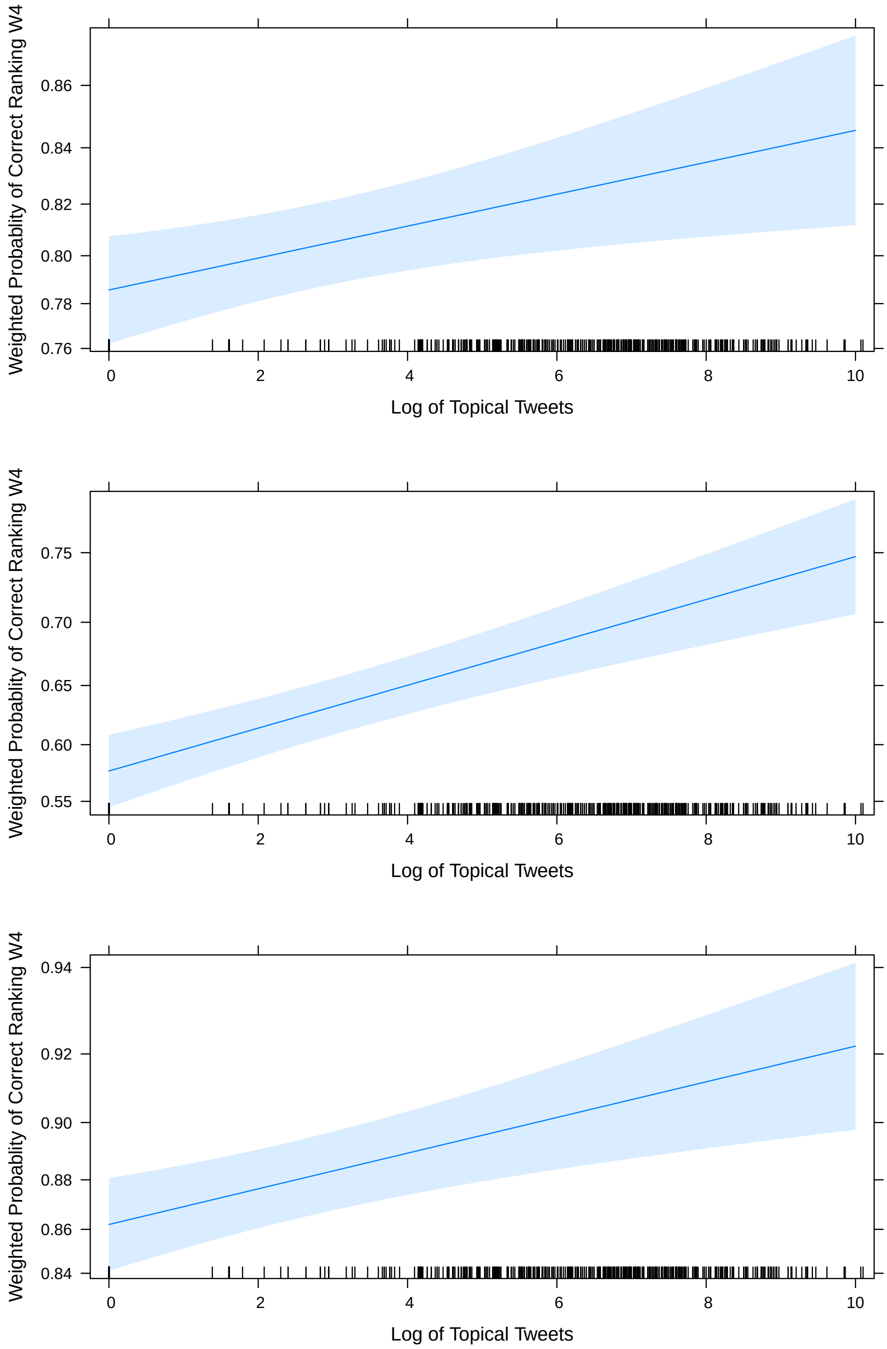


Figure 5: Weighted Replication of Figure 4: Effect of Topical Tweets by Source on Correctly Identifying Relative Party Placement

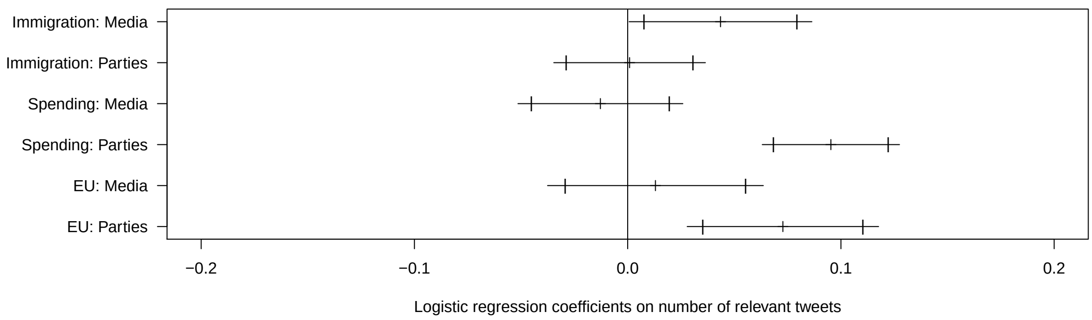


Figure 6: Weighted Replication of Figure 5: Effect of Topical Tweets on Knowledge of Issue-Relevant Facts

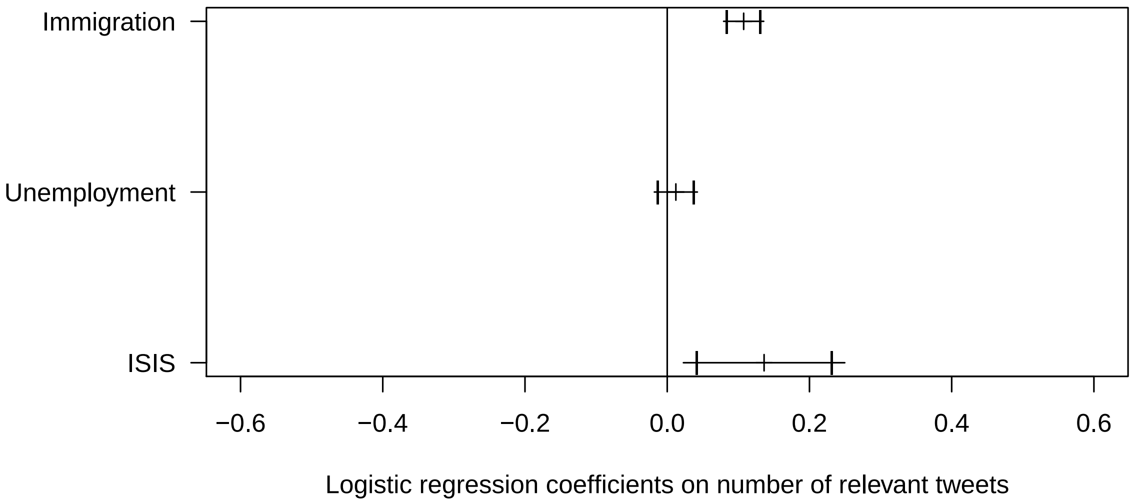


Figure 7: Weighted Replication of Figure 6: Effect of Topical Tweets by Source on Knowledge of Issue-Relevant Facts

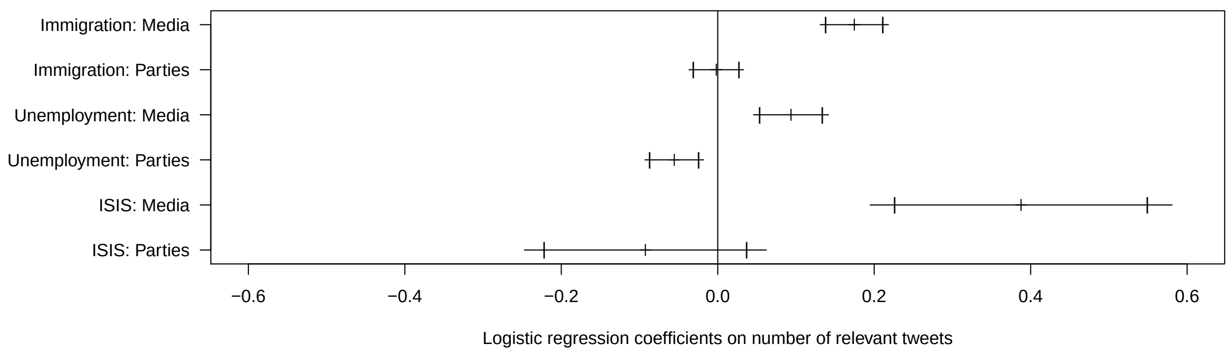


Figure 8: Weighted Replication of Figure 7: Effect of Topical Tweets by Source on Knowledge of Issue-Relevant Facton Unemployment

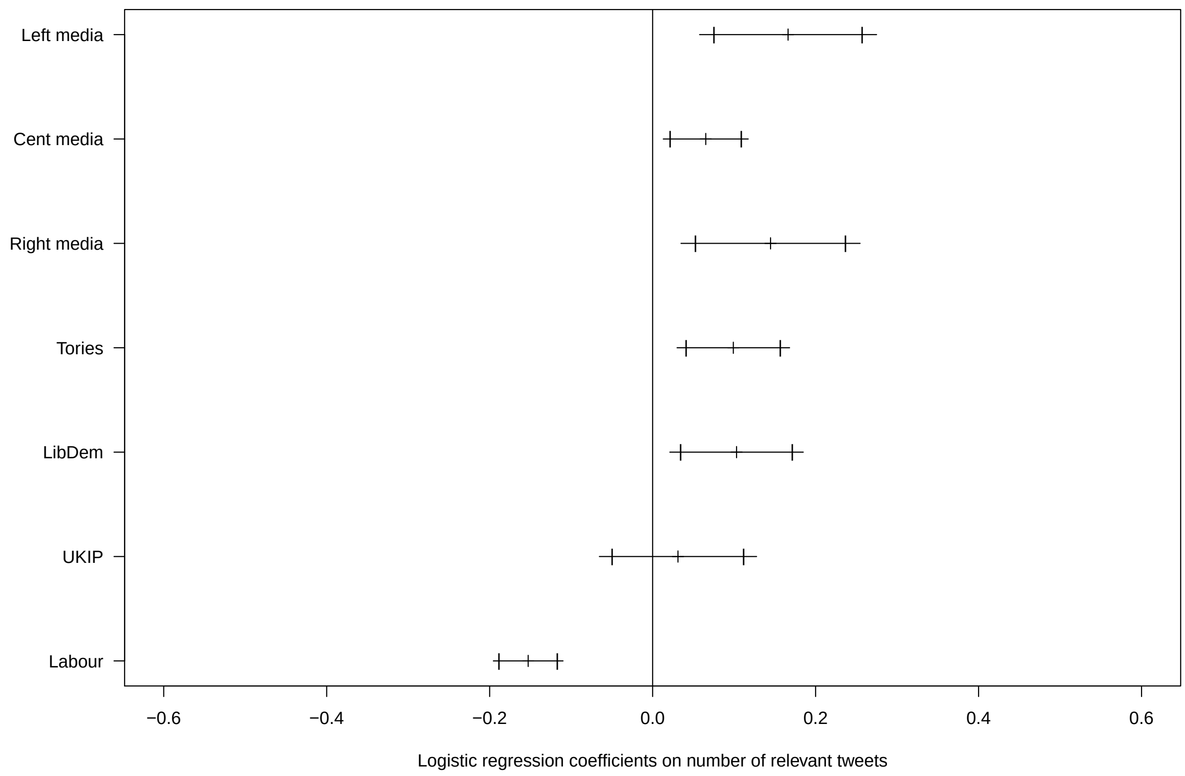


Figure 9: Weighted Replication of Figure 8: Effect of Topical Tweets by Source on Knowledge of Issue-Relevant Facton Immigration

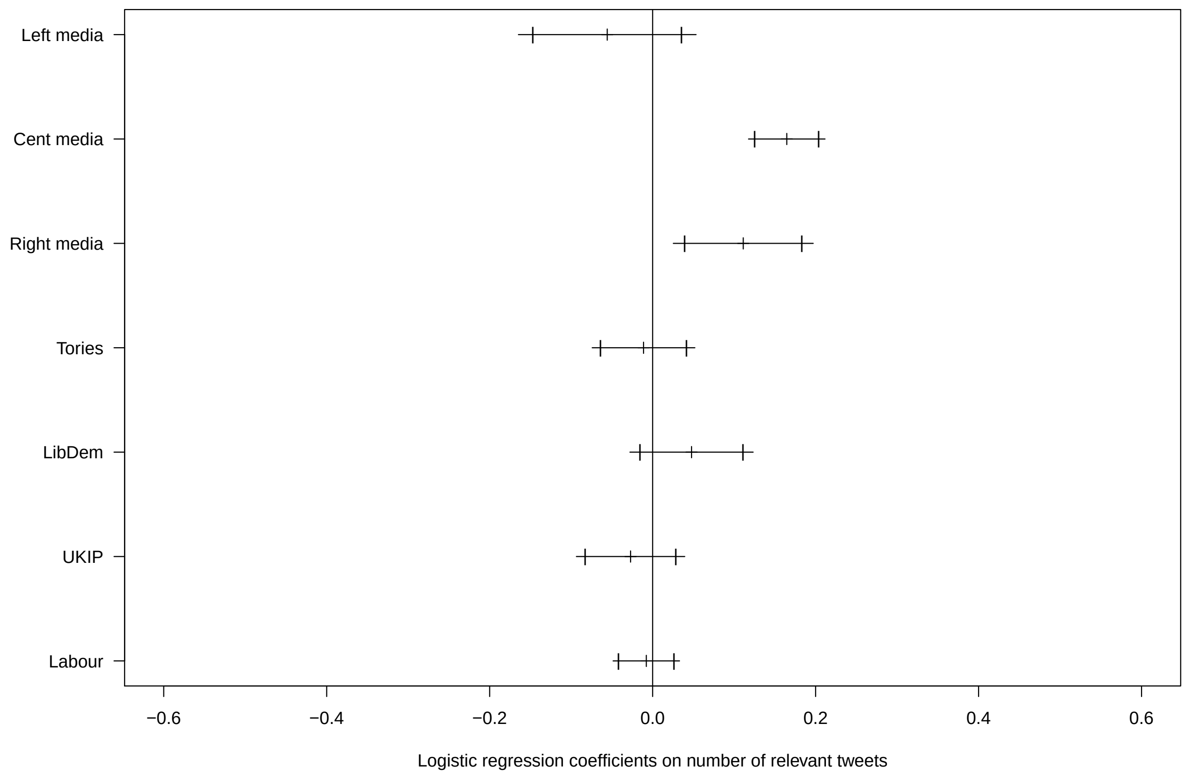


Table 10: Knowledge of Party Placements Among Non-Twitter Users

	EU, N= 407	
	Correct W1	Incorrect W1
Correct W4	38%	30%
Incorrect W4	7%	25%
Total W1	45%	55%

	Immigration, N= 392	
	Correct W1	Incorrect W1
Correct W4	48%	18%
Incorrect W4	10%	24%
Total W1	58%	42%

	Taxes and Spending, N= 293	
	Correct W1	Incorrect W1
Correct W4	24%	20%
Incorrect W4	17%	39%
Total W1	41%	59%

Cell entries are percentages for each possible combination of correct and incorrect answers across wave 1 and wave 4 of the party placement questions. The bottom line shows how difficult each question was showing the percentage correct in wave 1. Note that the large increase in accuracy about party placement in the EU is an artifact of how we coded responses. In Wave 4, the Liberal Democrats and Labour were too close together on this scale, so we coded either ordering of these two parties as correct; in Wave 1, the Liberal Democrats were sufficiently to the left of Labour.