Supplementary materials for:

"Does protest influence political speech? Evidence from UK Climate Protest, 2017–2019"

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Contents:

A Climate term dictionaries

climgram	**n**
"climate change"	7109
"climate emergency"	1927
"our planet"	1274
"climate crisis"	849
"tackle climate"	669
"tackling climate"	558
"climateemergency"	526
"climatechange"	372
"climate action"	260
"global warming"	205
"climate breakdown"	176
"climate justice"	144
"climateaction"	144
"climatecrisis"	141
"climate catastrophe"	130
"environment emergency"	113
"combat climate"	95
"climate change emergency"	88
"environmental challenges"	65
"environmental rights"	65
"stop climate"	61
"environmental crisis"	60
"sustainable future"	54
"sustainable development"	49
"environmental justice"	44
"environmental damage"	42
"fighting climate"	41
"climate emergencies"	40

Table APP-1: Core list of climate-related terms

climgram	**n**
"air pollution"	1335
"net zero"	898
"carbon emissions"	610
"green industrial revolution"	609
"zero carbon"	550
"plastic pollution"	538
"low carbon"	410
"zero emissions"	304
"renewable energy"	286
"co2 emissions"	257
"environmental protections"	256
"natural environment"	252
"plastic waste"	252
"green jobs"	242
"greenhouse gas"	225
"gas emissions"	222
"ban fracking"	204
"carbon neutral"	193
"environmental protection"	190
"heathrow expansion"	186
"carbon capture"	182
"climatedebate"	181
"single use plastics"	165
"green new deal"	155
"offshore wind"	152
"netzero emissions"	150
"clean energy"	141
"netzero"	141
"clean growth"	136
"cut emissions"	121
"decarbonise"	111
"plastic packaging"	107
"electric vehicles"	99
"reducing emissions"	96
"greenbrexit"	95
"toxic air"	92
"emissions target"	91
"reduce emissions"	90

"climate apprenticeships"	89
"climate targets"	88
"greennewdeal"	87
"improve air"	86
"carbon economy"	85
"plasticpollution"	85
"solar panels"	85
"low emission"	84
"greenindustrialrevolution"	82
"energy efficiency"	76
"cleangrowth"	71
"tackling plastic"	70
"eliminate plastic"	68
"worldenvironmentday"	67
"carbon future"	66
"electric cars"	59
"plasticfree"	59
"climate summit"	57
"environmental policy"	57
"reduce carbon"	57
"carbon reduction"	55
"plastic free"	55
"extreme weather"	54
"green finance"	54
"climateelection"	53
"cut carbon"	52
"paris climate"	52
"plastic bottles"	51
"reduce plastic"	51
"reduce pollution"	51
"green economy"	49
"green energy"	49
"renewables"	48
"microbeads"	48
"climate fund"	46
"climate leadership"	46
"environmental principles"	46
"decarbonisation"	42

"oneplanetsummit"	42
"reducing carbon"	42
"cutting emissions"	41
"environmental policies"	41
"against plastic"	40
"parisagreement"	40
"pollution crisis"	39

Table APP-2: Expanded list of climate-related terms

B Supplementary word-embedding analysis

In Figures 1 and 2 we see that over the course of our observation period there was a substantial increase in the incidence of climate protest. The main inflexion point here was March 15, 2019—the date of the first FFF Global Strike for Climate, when students from over 110 countries organized and skipped school to protest government inaction on climate change. We use this date as a demarcation point to consider how the substantive content of MPs' climate tweets changes after the climate protests. To do so, we apply another version of ALC embedding, which operates in a regression context.

We use the R package `conText` developed by Rodriguez et al. (2023). In this application, we again use the GloVe pre-trained embedding layer (Pennington et al. 2014). After applying a transformation matrix to downweight commonly appearing words, Rodriguez et al. (2023) show that we can then use the stacked embeddings of context words as the distributional representation of our target word, and make inferences about meaning by comparing embeddings in terms of distance in vector space.

We compute ALC embeddings for the target word `climate` as a function of one key covariate: a time dummy for pre- and post-March 15, 2019—the date of the first FFF Global Strike for Climate. We then identify the "nearest neighbour" words for `climate` before and after March 15, where nearest neighbours are taken as those words whose vector representation (in the pre-trained embedding) has lowest cosine distance to the implied embedding of our target word. The closer the cosine distance, the closer the words are in vector space, and the closer they can

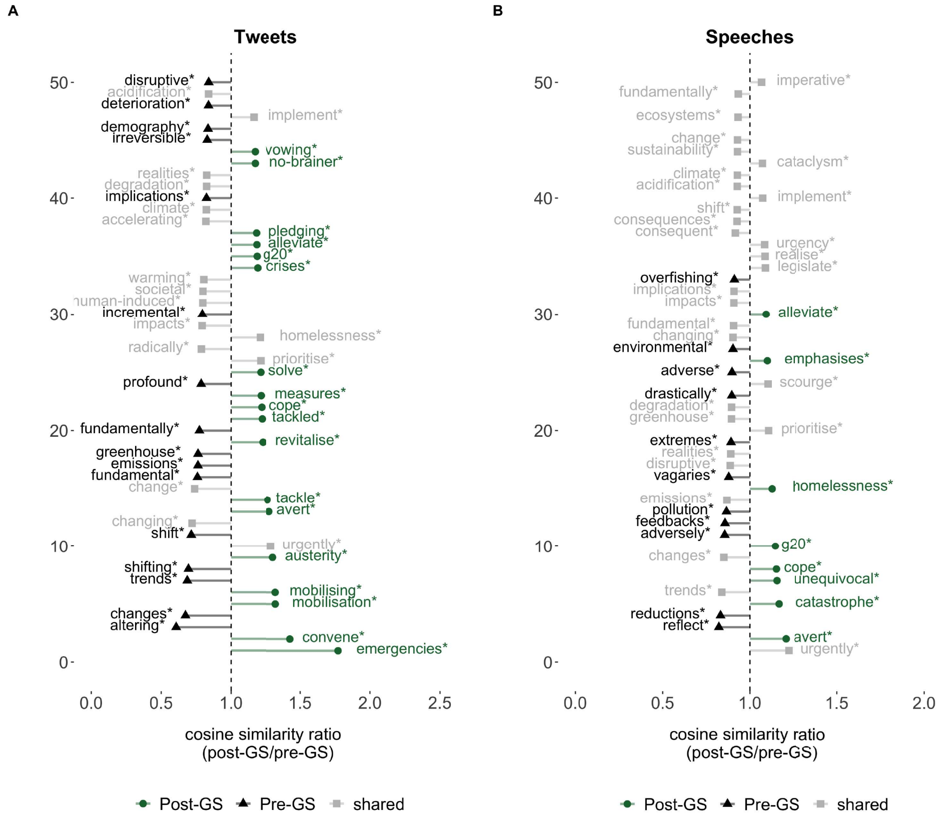

Figure APP-1: Changes in content of **(A)** MP tweets and **(B)** MP speeches before (pre-GS) and after (post-GS) the first FFF Global Strike for Climate on March 15, 2019. Words in green (black) appear among the top nearest neighbours of climate in the post-GS (pre-GS) period only; words in grey appear among the top nearest neighbours of climate in both periods.

be understood in meaning. Finally, a bootstrapping and permutation procedure, as described in Rodriguez et al. (2023), is used to obtain standard errors and identify any significant deviation in meaning between our two time periods.[1]

In Figure APP-1, we plot the cosine similarity ratio of the ALC embeddings for "climate" before and after the Global Strike for Climate for both MP tweets and speeches. A large cosine similarity ratio value indicates that a word is closer to the post-Global Strike understanding

[1]We also considered models using the date of a constituency's first FFF protest as our main explanatory variable, but this created very short post-period time windows for some MPs and introduced new temporal dependence into the data.

of "climate" than the pre-Global Strike understanding. Only words with significant deviations from one are displayed, where one indicates no difference in the cosine similarity ratio. Before the Global Strike, MPs tended to tweet about climate change descriptively in terms of its "profound" "implications" and "realities", while also discussing "incremental" "change" and "trends." Following the Global Strike for Climate, climate tweets shift from description toward crisis and advocacy: "avert[ing]" climate change becomes a key focus of discussion, the climate "crises" are "emergencies" around which we need to be "mobilising," and the UK government will "convene" with other "G20" countries, "vowing" new "measures" to "solve" climate change. A similar, if slightly less pronounced pattern can be seen in speeches, where talk of "changes," "reductions," and more general environmental concerns around "overfishing" turn, after the Global Strike for Climate, to talk of a "catastrophe" to be "avert[ed]" with "urgency."

C Regression models

In this section, we present regression results for heterogeneous treatment effects, binary measures of climate speech for all models presented in text, as well as the expanded dictionary of climate terms in tweets and speeches.

C.1 Heterogeneous treatment effects

The theoretical argument and results as presented to this point have focused on the average effect of protest across all MPs. Given that climate change is more of a valence issue than a polarized one in the UK, and that the FFF protests have received relatively favourable public opinion, we believe this is a plausible way to evaluate their effects. Nonetheless, it may still be the case that the effect of climate protests varies across MPs, with some MPs reacting more strongly. In particular, MPs that have already adopted pro-climate positions may be especially likely to respond to local protests, while MPs that have opposed climate action might be less so.

We now evaluate heterogeneous effects across legislators. We first consider whether MPs from the All-Party Parliamentary Group on Climate Change (APG) respond more than other MPs. Model 13 shows that, indeed, these MPs are more likely to tweet about climate change following protests. Model 14 also shows that these MPs are less likely to speak on climate change in the Commons, but the effect is very small substantively. Next, we consider whether Labour MPs react more strongly than Conservative MPs. Even with cross-party support in the UK for climate action, the Labour Party may be seen as more of an issue leader on climate. Furthermore, widespread protests express some dissatisfaction with the current government, and opposition (i.e., Labour) MPs may be more willing to support protests to ally against the government. Model 15 shows that Labour MPs do respond more in their tweets than Conservative MPs (the reference category), but Model 16 shows no equivalent difference in MPs' Commons speeches.[2] Models 17–20 consider heterogeneity amongst Conservative MPs. We find that the relatively pro-climate MPs that are members of the Conservative Environment Network (CEN) respond more to local protests than other Conservative MPs, while members of the Net Zero Scrutiny Group (NZSG), a group of Conservative MPs opposed to the government's net zero plans, do not differ from other Conservatives.[3] Finally, we interact climate protests with our measure of frontbench status to examine whether the most prominent MPs in our dataset respond differently. We find little indication that overall MP responsiveness is driven by prominent frontbench parliamentarians.

As well as showing some interesting heterogeneity among MPs, these results have two implications for interpreting our main findings.[4] First, they lend additional plausibility to our finding that protest increased MPs' climate-related tweeting. Second, they suggest that our null finding regarding protest's effect on parliamentary speech is not simply because the average effect is driven by lower responsiveness among certain subsets of MPs. Even when focusing

[2]An additional analysis does reveal that Labour MPs were more likely to attend climate strike protests—and tweet about them. Eighteen Labour MPs attended protests on twenty-two separate occasions; four Conservative MPs attended protests on four separate occasions. Full details of these MPs are listed in Supplementary Materials Table APP-18.

[3]Note that the Net Zero Scrutiny Group was formed in 2022, after our observation period, so this membership is post-treatment and should not be interpreted causally.

[4]It should be noted that these interaction terms cannot be interpreted causally themselves—they simply show that the causal effect of protest differs across subgroups. Those subgroups likely differ in other ways unmodelled here. For example, Labour and Conservative MPs typically represent systematically different constituencies.

	M13 Tweets	M14 Speeches	M15 Tweets	M16 Speeches	M17 Tweets	M18 Speeches	M19 Tweets	M20 Speeches	M21 Tweets	M22 Speeches
FFF	0.084**	-0.001	0.051**	0.000	0.044**	-0.001	0.075**	0.000	0.070*	-0.002
	(0.021)	(0.002)	(0.020)	(0.002)	(0.017)	(0.001)	(0.019)	(0.002)	(0.027)	(0.002)
FFF × APG	0.255*	-0.014**								
	(0.124)	(0.004)								
FFF × Labour			0.118*	-0.003						
			(0.049)	(0.004)						
FFF × CEN					0.125*	0.001				
					(0.054)	(0.006)				
FFF × NZSG							0.123	-0.004		
							(0.213)	(0.004)		
FFF × Frontbench									0.087	0.001
									(0.045)	(0.004)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit fixed effect	MP	MP	MP	MP	MP	MP	MP	MP	MP	MP
Time fixed effect	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week
Observations	505938	505938	452752	452752	241171	241171	241171	241171	452752	452752

Table APP-3: Heterogeneous effects of FFF protests on political speech. Local FFF protest interacted with MP characteristics; standard errors in parentheses; $* = p < 0.05$, $** = p < 0.01$.

on groups who might be more likely to respond positively to climate protest, we still only find effects on their online speech.

C.2 Anticipation and parallel trends

	R1A	R2A	R3A	R4A	R5A
Local FFF protest	0.116**	0.121*	0.138**	0.202**	
	(0.033)	(0.051)	(0.035)	(0.038)	
Tweets (daily sum)	0.004**	0.005**	0.005**	0.005**	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Cumulative FFF protests to date		0.009*			
		(0.004)			
FFF events × cumulative FFF protests		0.028			
		(0.023)			
FFF events × pre-period climate tweets			0.006**		
			(0.002)		
Placebo FFF protests from Sweden					−0.004**
					(0.001)
Observations	457 525	505 938	505 938	505 938	316 115
Unit fixed effect	MP	MP	MP	MP	MP
Time fixed effect	Year–week	Year–week	Year–week	Year–week	Year–week
Standard errors clustered by MP					
Outcome is count of climate tweets					
* $p < 0.05$, ** $p < 0.01$					

Table APP-4: Robustness tests for Fridays for Future protest on MPs' tweets

A, B Models lettered "A" use climate tweets as outcomes, and models lettered "B" use offline climate speeches in the House of Commons as outcomes

R1 We subset the dataset to take only the first local FFF protest per MP. We recover the same positive effect of protest on climate tweets

R2 We interact a count of cumulative local FFF protests per MP with the incidence of a local FFF protest. We recover the same positive effect of protest on climate tweets, and the interaction is not statistically significant

R3 We interact a count of an MP's climate tweets before their first local FFF protest with the

	R1B	R2B	R3B	R4B	R5B
Local FFF protest	−0.003**	−0.005	0.001	−0.003	
	(0.001)	(0.006)	(0.002)	(0.002)	
Speeches (daily sum)	0.006**	0.008**	0.008**	0.008**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Cumulative FFF protests to date		0.002**			
		(0.001)			
FFF events × cumulative FFF protests		0.000			
		(0.002)			
FFF events × pre-period climate speeches			−0.001*		
			(0.001)		
Placebo FFF protests from Sweden					−0.001**
					(0.000)
Observations	457 525	505 938	505 938	505 938	316 115
Unit fixed effect	MP	MP	MP	MP	MP
Time fixed effect	Year–week	Year–week	Year–week	Year–week	Year–week

Standard errors clustered by MP
Outcome is count of climate speeches
* $p < 0.05$, ** $p < 0.01$

Table APP-5: Robustness tests for Fridays for Future protest on MPs' speeches

incidence of a local FFF protest. We recover the same positive effect of protest on climate tweets, as well as a positive interaction effect indicating that MPs that tweeted more about climate in their "pre-period" respond more to local protests. "Pre-period" MP climate tweets is dropped from the estimation because it is perfectly collinear with the MP fixed effect

R4 We add MP-specific linear time trends at the monthly level. We recover the same positive effect of protest on climate tweets

R5 We add a placebo test for whether MPs tweet about climate in response to Greta Thunberg's school strike protests beginning in Sweden in August 2018. All Fridays from August 2018 to January 2019 are re-coded as "1" for all MPs. We do not find an effect of foreign protests on MPs' tweets, as the coefficient is nearly zero

C.3 Event study framework

In the main models in-text, we measure FFF protests in a time window approach—counting the number of protests over a specified, increasing number of days. This allows us to recover an effect of FFF protest on political speech if MPs respond over a few days rather than on the same day.

It is also common to study these kinds of processes in an event study framework. The event study creates a new set of indicators on either side of the local FFF protest event, which allows us to estimate any anticipation effects or pre-trends, as well as the persistence of an effect over time. We create time dummies for the five days on either side of the protest. These day dummies allow for a flexible treatment effect across days.

We use the following estimating equation:

$$\text{Climate Speech}_{i,t} = \sum_{h-5}^{H} \tau_h \mathbf{1}[t - \text{FFF}_{i,t} = h] + \gamma \mathbf{X}_{i,t} + \alpha_i + \delta_d + \epsilon_{i,t}$$

where i indexes MPs (and necessarily constituencies), t indexes days, d indexes our measures of time controls (year-by-week fixed effects in this specification), Climate Speech measures either the sum of climate tweets or the sum of climate speeches in Parliament, and $\mathbf{X}$ is a vector of covariates that contains the sum of an MP's speeches/tweets on that given day t. Note that in this specification we are measuring protest and speech at the daily-level t and controlling for temporal trends and shocks at a higher level of aggregation d.

The key terms of the event study are h, which indexes the five days prior to the five days after the protest, including 0—the day of the protest—for 11 day dummies **1**. τ_h recovers the effect of protest on speech on day h on either side of the protest. We estimate this using ordinary least squares (OLS) regression with standard errors clustered on the MP.

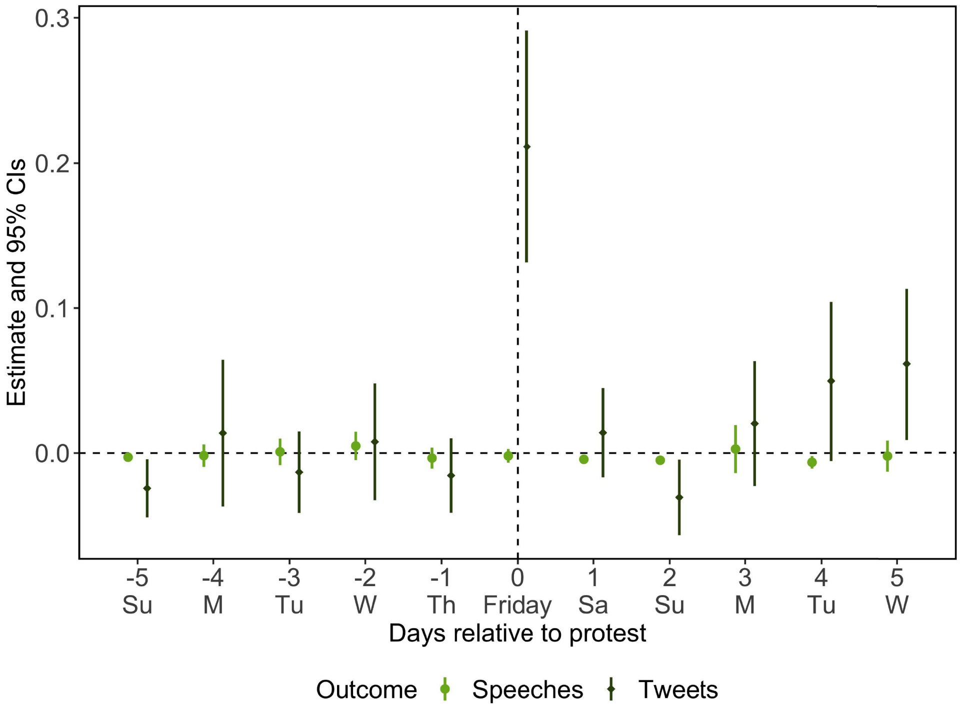

Figure APP-2: Effect of FFF protests on climate speeches and tweets

We show these estimates for climate tweets and climate speeches in Parliament in figure APP-2. In the event study specification, we find a large effect on the day of the protest, which mirrors our results in figure 3 in-text. We find no sign of anticipation effects, where MPs withhold and mention climate change less before the protests. We also find a short-lived effect of protest, with most of the response taking place on the day of the protest and estimates near zero on other days.

C.4 Changes in volume of speech over time

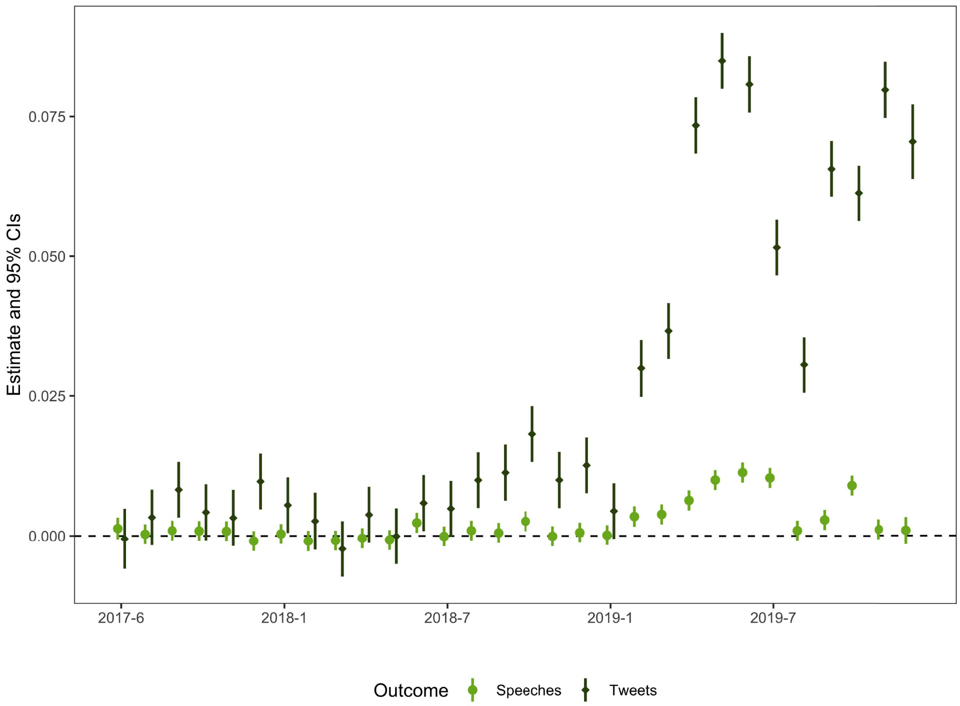

Figure APP-3: Volume of MP climate tweets and speeches increase over time, with tweets increasing more than speeches. Estimates are the year-by-month fixed effects in regression of speech (tweets) on year–month dummies controlling for MP-level count of total speeches (tweets), without FFF events modelled.

C.5 Binary measures of climate tweets and speeches

	B1	B2	B3	B4
FFF Protest	0.070**	0.070**	0.060**	0.060**
	(0.010)	(0.010)	(0.010)	(0.010)
Covariates	None	Frontbench	None	Frontbench
Unit fixed effect	MP	MP	MP	MP
time fixed effect	Year–month	Year–month	Year–week	Year–week
Observations	505938	505938	505938	505938
FFF Protest	0.070**	0.070**	0.060**	0.060**
	(0.010)	(0.010)	(0.010)	(0.010)

Table APP-6: Main models: Binary measure of climate tweets

	B5 Tweets	B6 Speeches	B7 Tweets	B8 Speeches	B9 Tweets	B10 Speeches
FFF Protest	0.060**	-0.002	0.054**	-0.001	0.021	0.007
	(0.010)	(0.002)	(0.019)	(0.009)	(0.014)	(0.006)
Covariates	Frontbench	Frontbench	Frontbench	Frontbench	Frontbench	Frontbench
Unit of observation	Daily	Daily	Weekly	Weekly	Sitting days	Sitting days
Unit fixed effect	MP	MP	MP	MP	MP	MP
Time fixed effect	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week
Observations	505938	505938	86623	86623	199738	199738

Table APP-7: Online and offline speech: Binary measures of climate tweets and speeches

	B13 Tweets	B14 Speeches	B15 Tweets	B16 Speeches	B17 Tweets	B18 Speeches	B19 Tweets	B20 Speeches	B21 Tweets	B22 Speeches
FFF	0.051**	-0.001	0.038**	0.000	0.028**	-0.001*	0.054**	-0.001	0.043**	-0.002
	(0.010)	(0.002)	(0.012)	(0.002)	(0.010)	(0.000)	(0.012)	(0.002)	(0.013)	(0.002)
FFF × APG	0.101*	-0.011**								
	(0.048)	(0.003)								
FFF × Labour			0.059*	-0.001						
			(0.024)	(0.004)						
FFF × CEN					0.098**	0.002				
					(0.032)	(0.006)				
FFF × NZSG							0.024	-0.002		
							(0.101)	(0.002)		
FFF × Frontbench									0.054*	0.002
									(0.023)	(0.004)
Observations	505938	505938	452752	452752	241171	241171	241171	241171	452752	452752
Unit fixed effect	MP	MP	MP	MP	MP	MP	MP	MP	MP	MP
Year–week fixed effect	X	X	X	X	X	X	X	X	X	X

Table APP-8: Heterogeneous effects: Binary measures of climate tweets and speeches

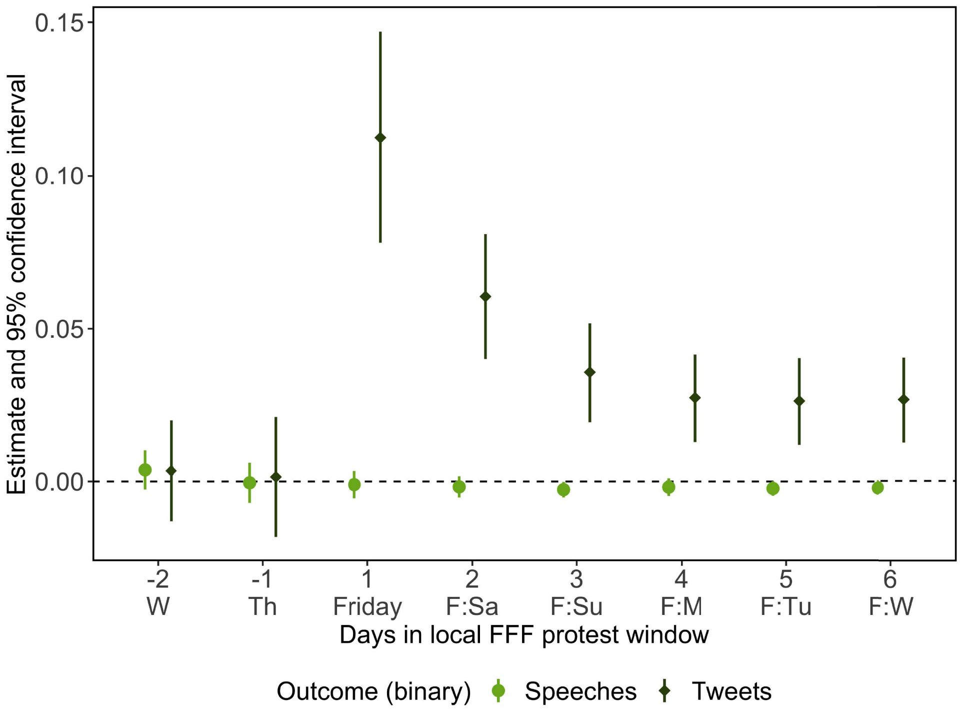

Figure APP-4: Binary measures of climate speech

C.6 Expanded dictionary of climate terms

	Z1	Z2	Z3	Z4
FFF Protest	0.039**	0.039**	0.033**	0.033**
	(0.012)	(0.012)	(0.012)	(0.012)
Covariates	None	Frontbench	None	Frontbench
Unit fixed effect	MP	MP	MP	MP
time fixed effect	Year–month	Year–month	Year–week	Year–week
Observations	505938	505938	505938	505938

Table APP-9: Main models: Expanded measure of climate tweets

	Z5	Z6	Z7	Z8	Z9	Z10
FFF Protest	0.033**	-0.003	0.004	-0.008	0.021	0.016
	(0.012)	(0.002)	(0.048)	(0.010)	(0.021)	(0.012)
Covariates	Frontbench	Frontbench	Frontbench	Frontbench	Frontbench	Frontbench
Unit of observation	Daily	Daily	Weekly	Weekly	Sitting days	Sitting days
Unit fixed effect	MP	MP	MP	MP	MP	MP
Time fixed effect	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week
Observations	505938	505938	86623	86623	199738	199738

Table APP-10: Online and offline speech: Expanded measure of climate tweets

	Z13 Tweets	Z14 Speeches	Z15 Tweets	Z16 Speeches	Z17 Tweets	Z18 Speeches	Z19 Tweets	Z20 Speeches	Z21 Tweets	Z22 Speeches
FFF	0.020	-0.002	0.017	0.000	0.015	0.000	0.027*	0.000	0.005	-0.001
	(0.011)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)
FFF × APG	0.137*	-0.003								
	(0.063)	(0.008)								
FFF × Labour			0.020	-0.006*						
			(0.026)	(0.003)						
FFF × CEN					0.049	-0.002				
					(0.030)	(0.006)				
FFF × NZSG							0.062	-0.009		
							(0.127)	(0.007)		
FFF × Frontbench									0.056*	-0.004
									(0.028)	(0.003)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit fixed effect	MP	MP	MP	MP	MP	MP	MP	MP	MP	MP
Time fixed effect	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week	Year–week
Observations	505938	505938	452752	452752	241171	241171	241171	241171	452752	452752

Table APP-11: Heterogeneous effects: Expanded measure of climate tweets

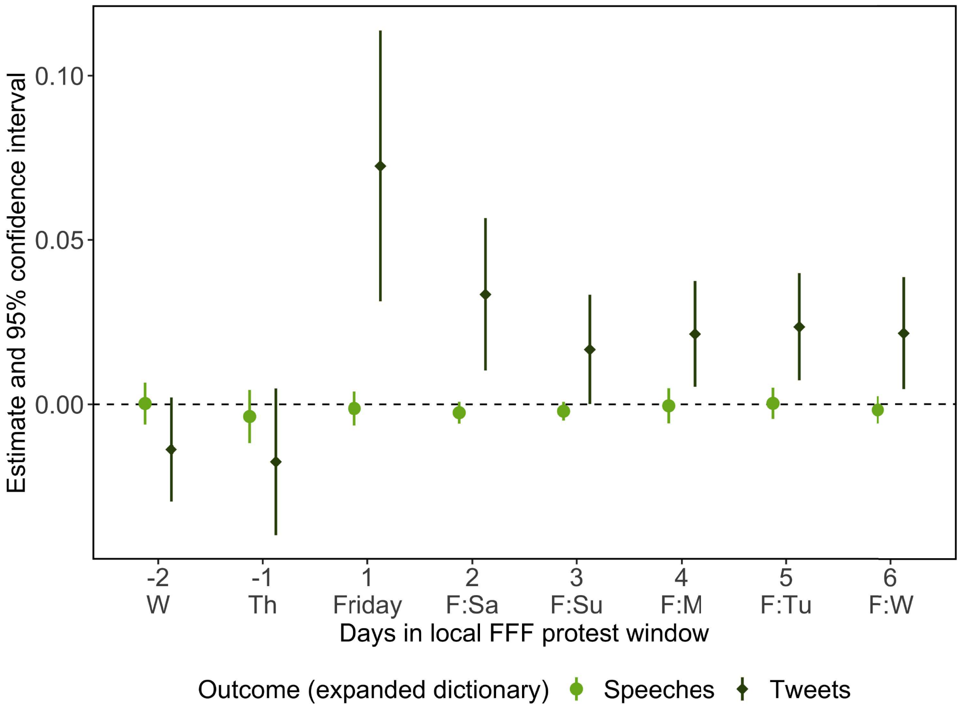

Figure APP-5: Expanded dictionary of climate speech

D Full regression tables

	Outcome: Tweets							
FFF (day of:lead 2)	−0.010							
	(0.014)							
FFF (day of:lead 1)		−0.022						
		(0.013)						
FFF (day of)			0.211**					
			(0.040)					
FFF (day of:lag 1)				0.109**				
				(0.022)				
FFF (day of:lag 2)					0.063**			
					(0.015)			
FFF (day of:lag 3)						0.051**		
						(0.014)		
FFF (day of:lag 4)							0.050**	
							(0.015)	
FFF (day of:lag 5)								0.052**
								(0.016)
Sum tweets	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	505 385	505 938	506 491	505 938	505 385	504 832	504 279	503 726
MP fixed effect	X	X	X	X	X	X	X	X
Year-week fixed effect	X	X	X	X	X	X	X	X

* p < 0.05, ** p < 0.01

Table APP-12: Full regression table for tweets outcomes in figure 3

	Outcome: Speeches							
Sum speeches	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FFF (day of:lead 2)	0.001							
	(0.003)							
FFF (day of:lead 1)		−0.003						
		(0.004)						
FFF (day of)			−0.002					
			(0.002)					
FFF (day of:lag 1)				−0.002				
				(0.002)				
FFF (day of:lag 2)					−0.003*			
					(0.001)			
FFF (day of:lag 3)						−0.002		
						(0.002)		
FFF (day of:lag 4)							−0.003	
							(0.002)	
FFF (day of:lag 5)								−0.003
								(0.002)
Observations	505 385	505 938	506 491	505 938	505 385	504 832	504 279	503 726
MP fixed effect	X	X	X	X	X	X	X	X
Year-week fixed effect	X	X	X	X	X	X	X	X

* p < 0.05, ** p < 0.01

Table APP-13: Full regression table for speeches outcomes in figure 3

	M5	M6	M7	M8	M9	M10
FFF (window: $_{t:t+1}$)	0.109**	−0.002				
	(0.022)	(0.002)				
FFF events (weekly)			0.152*	−0.009		
			(0.071)	(0.014)		
Sum FFF events (window, lag 1)					0.021	0.007
					(0.027)	(0.010)
Sum tweets	0.005**					
	(0.001)					
Sum speeches		0.008**				
		(0.001)				
Sum tweets (weekly)			0.005**			
			(0.001)			
Sum speeches (weekly)				0.007**		
				(0.001)		
Sum tweets (window)					0.007**	
					(0.001)	
Sum speeches (window)						0.007**
						(0.001)
Frontbench	0.015*	0.000			0.053**	0.000
	(0.006)	(0.001)			(0.020)	(0.003)
Frontbench (week)			0.104*	−0.001		
			(0.044)	(0.007)		
Window length					−0.002	0.000
					(0.002)	(0.000)
Observations	505 938	505 938	86 623	86 623	199 738	199 738
MP fixed effect	X	X	X	X	X	X
Year-week fixed effect	X	X	X	X	X	X

* p < 0.05, ** p < 0.01

Table APP-14: Full regression table for table 2

	M11	M12
FFF (September)	−0.016	−0.025
	(0.021)	(0.022)
FFF (cumulative, 2019-10-07)	−0.004	
	(0.008)	
FFF (Sept. × cumulative, 2019-10-28)		0.017
		(0.010)
FFF (cumulative, 2019-10-28)		−0.008
		(0.008)
FFF (Sept. × cumulative, 2019-10-07)	0.017	
	(0.009)	
Climate speeches (cumulative)	0.004**	0.004**
	(0.001)	(0.001)
Cumulative speeches	−0.001	0.003
	(0.007)	(0.007)
Speak (2019-10-07)	−0.011	
	(0.013)	
Speak (2019-10-28)		0.007
		(0.013)
Frontbench	0.007	−0.014
	(0.013)	(0.014)
Democratic Unionist Party	0.009	−0.007
	(0.051)	(0.054)
Green Party	−0.176	−0.191
	(0.137)	(0.144)
Labour	0.016	0.021
	(0.013)	(0.013)
Liberal Democrat	0.055	−0.036
	(0.039)	(0.041)
Plaid Cymru	0.008	−0.003
	(0.077)	(0.080)
Scottish National Party	0.020	0.035
	(0.024)	(0.025)
(Intercept)	−0.003	−0.014
	(0.036)	(0.039)
Observations	550	550

* $p < 0.05$, ** $p < 0.01$

Table APP-15: Full regression table for table 3

E Descriptive statistics

In this section we provide details on the types of movement organizations coordinating protest efforts during the FFF campaign. We also detail the type and content of climate-related tweets posted by MPs.

E.1 Movement organizations

Of the 760 events in our FFF event dataset, we were able to retrieve organizer information on 145. The reason that we could only retrieve organizers for this number is that many of the links used to organize protests expired soon after the protest took place. We cannot discount the possibility that this introduces systematic bias—as it could be that some organizations deleted event information more routinely than others. Our counts nonetheless tally with qualitative and quantitative accounts contained in Wahlström et al. (2019) and de Moor et al. (2020). Counts from the events for which we could retrieve organizer information are displayed in Table APP-16.

Organization	**n**	
1	Youth Strike 4 Climate	83
2	Student Climate Network	53
3	XR	31
4	Youth Climate Coalition	27
5	Earth Strike International	22
6	Individuals	18
7	FFF	16
8	Bath Youth Climate Alliance	5
9	Green Party	4
10	Youth4Climate	4
11	Bath People and Planet	3
12	Cambridge Climate Justice	3
13	Friends of the Earth	3

14	United Nations Association Coventry	3
15	11th Hour Strike for the Climate	2
16	Climate Action St Andrews	2
17	CoventryCAN	2
18	Lancaster Youth for Environment	2
19	Oxford Climate Justice Campaign	2
20	School.CO2lutions	2
21	Undeb Bangor	2
22	Youth Climate Summit	2
23	Aberdeen University Students' Union	1
24	Amnesty St Andrews	1
25	Ashmount Primary School	1
26	Aviemore Climate Hub	1
27	Bristol Environmental Activists Together	1
28	Campaign against Climate Change	1
29	Christ Church Students' Union	1
30	Climate Action Network	1
31	Climate Strike Leicester	1
32	College and Community Life	1
33	Cornish Climate Change	1
34	Derby Climate Coalition	1
35	Earth Justice Nottingham	1
36	Eco Action Families	1
37	Eco March Northampton	1
38	EcoEd2030	1
39	Environment Subcommittee St Andrews	1
40	FACE	1
41	Fight 2 Unite Thanet	1
42	Frederick Bird Primary School	1
43	Friends of Northants Green Activism	1
44	Global Justice Now Glasgow	1
45	Global Strike for Climate	1
46	Greening Steyning	1
47	Greenpeace Glasgow	1
48	IBike London	1
49	Jersey Students for Environmental Justice	1
50	Kent Union	1
51	Lambeth Save our Services	1
52	Lambeth Trades Council	1
53	Lambeth UNISON	1

54	Litter Kickers	1
55	London Cycling Campaign	1
56	Mothers rise up	1
57	NUS	1
58	Newcastle People and Planet	1
59	Northeast England Climate Justice Coalition	1
60	Parents for Future Global	1
61	Portland 4 the Planet	1
62	RSPB	1
63	Roade Climate Strikes	1
64	South East Climate Alliance	1
65	Student Activists Cambridge	1
66	Swindon Solidarity	1
67	Unison Glasgow	1
68	UoG Green Team	1
69	WWF	1
70	Whitby Climate Change March	1
71	Wildlifetek	1
72	Wyre Forest Vegans	1
73	Youth Campaign against Climate Change	1

Table APP-16: Organization types

In Table APP-17 we detail information about the most common organizers of FFF protests. FFF functioned as the umbrella campaign for many organizations, some of which emerged in its wake and some of which predated the protests. Organizers were most often listed as co-organizers on Facebook event pages. Qualitative information on each of the organizations indicates that many had the autonomy to organize locally. This meant many would co-mobilize with organizations that shared the broader goals of the FFF campaign. Examples of how organizer information was detailed are provided in Figure APP-6.

Organization	Details	Sources
Youth Strike 4 Climate	Movement that constitutes part of the broader UK Youth Climate Coalition. Some protests are advertised as organised by "Youth Strike 4 Climate" subgroups while others are advertised as organised by the UK Youth Climate Coalition. The organization campaigns on the broader platform of the Fridays for Future movement and pursues climate strikes as mode of protest action. The movement is also affiliated to the UK Student Climate Network. Youth Strike 4 Climate has numerous regional and local groups. The most prominent of these was the Bristol Youth Strike 4 Climate who hosted Greta Thunberg at a protest. The Bristol group now functions as a separate entity.	`https://www.bristolys4c.org/about-us` and `https://en.wikipedia.org/wiki/Bristol_Youth_Strike_4_Climate` and `https://www.ukycc.com/youth-strike-4-climate`
Student Climate Network	The UK Student Climate Network was founded on December 1, 2018 by school students inspired by the Campaign Against Climate Change movement. It became a large network of advocacy groups with over 100 local groups across the UK. They take inspiration from Greta Thunberg and the Fridays for Future movement. Some of the movements they provide support to include groups under the "Youth Strike 4 Climate" or "Fridays for Future" or "XR" banners. They list as official partner movements: Scottish Youth Climate Strike who coordinate the "Youth Strike 4 Climate" movement in Scotland; Youth Climate Association Northern Ireland who do the same in Northern Ireland; and Fridays for Future.	`https://ukscn.org/about-us/` and `https://ukscn.org/local-strike-groups/`
Youth Climate Coalition	The UK Youth Climate Coalition is closely tied to groups describing themselves as "Youth Strike 4 Climate" entities. They actively supported both "Fridays for Future-" and "Youth Strike 4 Climate-" sponsored events. The organization nonetheless predates these organisations and campaigns as it was founded in 2008. The organization is staffed principally by young volunteers aged 18-29. Its function is to coordinate climate change advocacy groups in the UK.	`https://www.ukycc.com/` and `https://en.wikipedia.org/wiki/UK_Youth_Climate_Coalition`
Earth Strike International	Earth Strike International is an international group founded with the specific goal of mobilising a global strike for climate action. In this, they were particularly active in the September 2019 global wave of climate strikes. In the UK, the organization has worked alongside XR, Fridays for Future, and Youth Strike 4 Climate. It also distinguishes itself for its focus on mobilising labour unions and working-class support as well as advancing anti-capitalist goals.	`https://en.wikipedia.org/wiki/Earth_Strike` and `https://earth-strike.co.uk/about/faqs/`
XR	XR or Extinction Rebellion is a global movement that began in the UK in Stroud as a group that emerged from a previous organization called "Rising Up!" The group achieved notoriety for their pursuit of nonviolent civil disobedience that was often disruptive and headline-grabbing. The movement is decentralised, consisting of multiple local groups that claim affiliation to the cause. The movement also consists of many subgroups such as "XR Families" or "XR Youth." XR is perhaps most notable for mobilising individuals with little prior experience of protest—in particular, senior citizens.	`https://en.wikipedia.org/wiki/Extinction_Rebellion` and `https://extinctionrebellion.uk/` and `https://cusp.ac.uk/themes/p/xr-study/`
FFF	Fridays for Future (or FFF) is variously referred to as the "School Strike for Climate," "Youth for Climate" "Climate Strike," and "Youth Strike for Climate" movement. The movement emerged from the solitary protest of Greta Thunberg in August, 2018. It functions as an umbrella organization animating many of the activities of the groups listed above. Actions listed under the banner of Fridays for Future include local actions organised by the groups listed here and in the full Table APP-16 above. Some groups function locally under the banner of Fridays for Future rather than any of the affiliated groups.	`https://fridaysforfuture.org/action-map/map/` and `https://fridaysforfuture.org` and `https://en.wikipedia.org/wiki/School_Strike_for_Climate` and `https://osf.io/asruw/`

Table APP-17: Main climate organization profiles

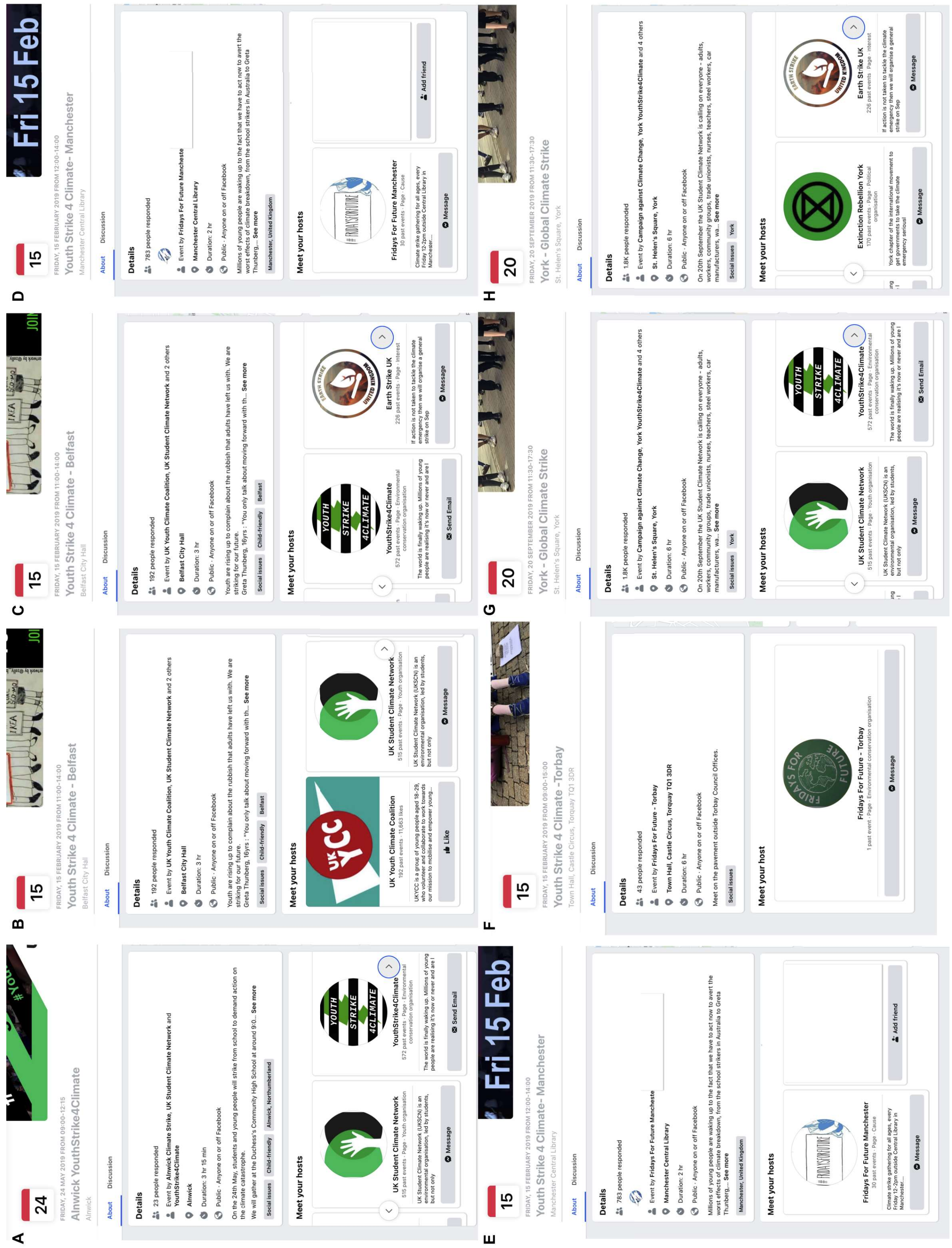

Figure APP-6: **A-H**: Examples of protest events on Facebook with organizer information.

To determine the extent to which MPs are participating in protests themselves, we filter our Twitter data by the date and location of known protests within MP constituencies. We then code this sample of tweets according to tweet text, image, and video content. We find that 18 Labour MPs attended a total of 22 separate protest events while 4 Conservative MPs attended 4 separate protest events.

Name	Party	Protests attended
Douglas Ross	Conservative	1
George Freeman	Conservative	1
Neil O'Brien	Conservative	1
Richard Benyon	Conservative	1
Caroline Lucas	Green Party	1
Chris Williamson	Labour	1
Eleanor Smith	Labour	1
Hilary Benn	Labour	1
Karl Turner	Labour	1
Matt Rodda	Labour	1
Mohammad Yasin	Labour	1
Mr Ben Bradshaw	Labour	1
Ms Diane Abbott	Labour	1
Paul Blomfield	Labour	1
Sandy Martin	Labour	1
Sir Lindsay Hoyle	Labour	1
Dr Roberta Blackman-Woods	Labour	2
Matt Western	Labour	2
Thangam Debbonaire	Labour	2
Dr David Drew	Labour (Co-op)	1
Mr Barry Sheerman	Labour (Co-op)	1
Rachael Maskell	Labour (Co-op)	1
Luke Pollard	Labour (Co-op)	2
Tim Farron	Liberal Democrat	2
Wera Hobhouse	Liberal Democrat	4

Table APP-18: Number of protests attended by MPs of different parties in Twitter data

F References

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