

Supplementary Information:  
Do fossil fuel firms reframe online climate and sustainability  
communication? A data-driven analysis

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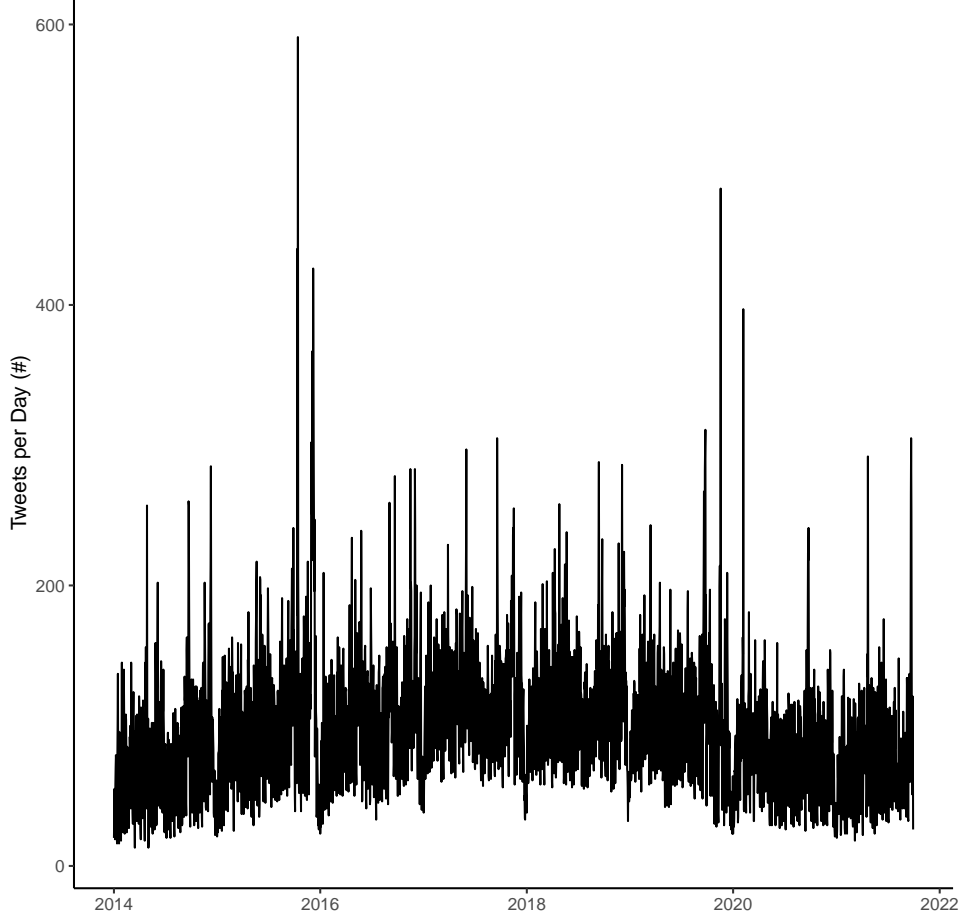
## Supplementary Section 1 Twitter Data

In Supplementary Table 1 we provide the complete list of the 8 non-governmental organizations (NGOs), the 14 intergovernmental organizations (IGOs), and the 8 fossil fuel firms (industry) and their respective follower counts (until September 2021) analyzed in our study. We used the global Twitter handles (usernames) of the organizations. References are presented in “Data Source” in the Method section of the manuscript.

Supplementary Table 1: Twitter usernames and follower count (until September 2021) of stakeholders used in this study

Organisation	Username	Followers (in thousands)
Non-governmental organizations		
350.org	350	393.2
C40Cities	c40cities	112.1
Climate Action Network International	CANIntl	42.1
Climate Group	ClimateGroup	156.5
Extinction Rebellion	ExtinctionR	386.8
Friend of Earth	foe_us	219.9
International Indigenous network	IENearth	82.7
Julies Bicycle	JuliesBicycle	11.4
Natural Resources Defence Council	NRDC	344.5
Project Drawdown	ProjectDrawdown	47.5
World Wildlife Fund	World_Wildlife	1400
Fridays for Future	Fridays4future	143.4
Greenpeace	Greenpeace	1800
La Via Campesina	via_campesina	25.9
Intergovernmental organizations		
Climate Innovation Fund	CIF_Action	21.1
EU Environment	EU_ENV	129.80
Intergovernmental Panel on Climate Change	IPCC_CH	327.40
International Union for Conservation of Nature	IUCN	186.1
Global Environment Fund	theGEF	80.60
United Nations Environment Programme	UNEP	1100
United Nations Framework Convention on Climate Change	UNFCCC	878.7
World Meteorological Organization	WMO	145.6
Fossil Industry		
BHP Billiton	bhp	56.1
British Petroleum	bp_plc	106.7
Chevron	Chevron	374.8
Conoco Phillips	conocophillips	163.6
ExxonMobil	exxonmobil	328.1
Peabody Energy	peabodyenergy	8.7
Total Energies	TotalEnergiesPR	16
Shell	Shell	566.2
Total followers		9655.5

Supplementary Figure 1 provides the time series of the total number of tweets per day across the stakeholder groups that we collected and analyzed in this study between 2014-2021.



Supplementary Figure 1: Tweets Per Day

## Supplementary Section 2 JST Evaluation

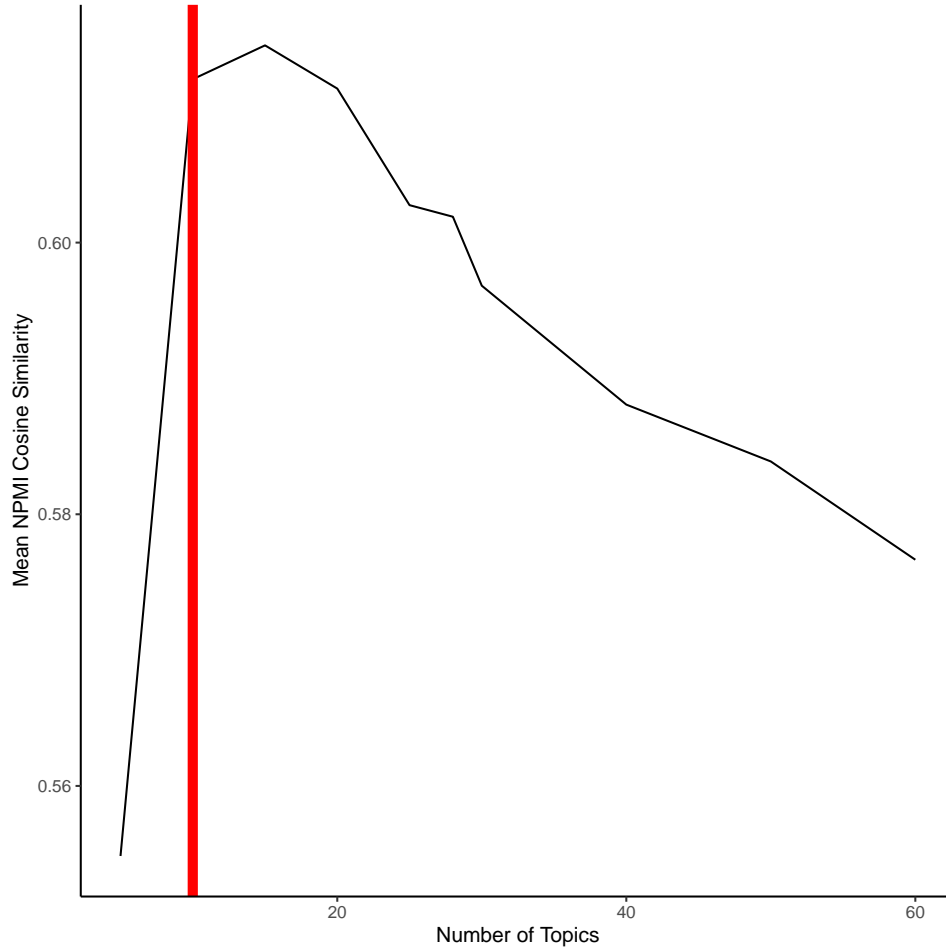
In addition, our JST model relied on exchangeability and a bag-of-words approach to speech that made the model mutually exclusive to the order of the words as the sentiment-topics were discovered across the stakeholder groups. It was done to optimize the computation costs with the coherence measure of the sentiment-topic clusters. A similar optimization approach was also taken by [2, 3]. Our pseudo-code for the data-generation process for the documents is summarized as follows:

1. For each tweet  $t$ , choose a distribution  $\pi_t \sim \text{Dirichlet}(\gamma)$ . Where,  $pi_t$  is a multinomial distribution over sentiments for each document drawn from a Dirichlet prior.
2. For each sentiment label  $j$  under tweet  $t$ , choose a topic distribution  $\theta \sim \text{Dirichlet}(\alpha)$ . Where,  $\theta$  is a multinomial distribution (drawn from a Dirichlet prior) over topics for each tweet conditional over a sentiment.
3. For each word  $w_i$  in tweet  $t$ ,
  - (a) Choose a sentiment label  $j_i$  from  $pi_t$ .
  - (b) Choose a topic label  $k_i$  from  $\theta_{t,j_i}$ .
  - (c) Choose a word  $w_i$  from the distribution,  $\phi_{j_i,k_i}$  over words defined by the topic  $k_i$  and sentiment  $j_i$ . Here,  $\phi_{j_i,k_i}$  is a distribution over word given being in sentiment label  $j_i$  and topic label  $k_i$  under sentiment  $j_i$ .

As a Bayesian hierarchical mixture model, we consider the hyperparameter  $\alpha$  as the prior concentration of the sentiment-topic  $k_i$  for a document before having seen any documents from the corpus. Similarly, hyperparameter

$\beta$  is the prior concentration of the sentiment-topic  $j$  for a word before any words from the corpus are observed. The hyperparameter  $\gamma$  is the prior concentration of the sentiment labels sampled under a document before having seen any documents.

We select the number of topics based on the inflection point beyond which increases in coherence are small. Based on this criterion, we select 28 topics. To arrive at this number, we tuned the model starting from 5 topics and 10 topics increasing in increments of 10 up to 60 topics. Realizing the inflection point was between 10 topics, we selected it as  $k$ . Supplementary Figure 2 shows that there is an inflection point at 10 topics, for 30 sentiment-topics. Supplementary Table 2 illustrates the top 5 tokenized words for the 30 sentiment-topics. Supplementary Table 3 shows the tweet with the highest probability of being labeled as a particular topic. This tweet is emblematic in that it is the most likely tweet to exemplify the topic.



Supplementary Figure 2: Coherence by Topic

Supplementary Table 2: Top 5 Topic Words

	1	2	3	4	5
Fight Climate Change	climat	action	crisi	justic	climat_crisi
Industry Supports STEM	chevron	support	stem	mt	team
Protect Endangered Species	speci	endang	wildlif	protect	save
Job Offers	job	offer	offr	job_offer	demploi
Indigenous Rights	coal	forest	indigen	right	plant
Gas Station Customer Service	parti	pass	contact	dm	station
IPCC	ipcc	climatechang	report	climat	event
Renewables	energi	renew	solar	power	clean
Stop toxic/plastic waste	food	plastic	pesticid	wast	ocean
Climate Action	climat	action	cop21	parisagr	pari
Air Pollution	air	pollut	water	clean	air_pollut
Stop XL Pipeline	pipelin	nokxl	sand	keyston	tar
Tackle Climate Change	climat	chang	climat_chang	fight	action
Corporate Sustainability	food	sustain	environ	system	futur
Extinction Rebellion	climat	govern	extinctionrebellion	ecolog	pm
Twitter Engagement	energi	carbon	electr	renew	busi
Protect Biodiversity	forest	biodiv	thegef	natur	ecosystem
Climatological Changes	global	warm	sea	record	rise
Media Engagement	live	watch	question	energi	tune
Share Pictures of Environment	day	photo	world	check	video
Extreme Weather	weather	extrem	flood	climat	climatechang
Emission Reduction	emiss	reduc	carbon	gas	co2
Promoting Company Website	chevron	site	check	live	career
Divest Fossil Fuels	fuel	fossil	fossil_fuel	climat	industri
Mayors' Actions- City Policy	citi	climat	mayor	action	c40
Gas Company Advertising	energi	oil	gas	bp	product
Oppose Trump Drilling Policies	oil	drill	land	arctic	trump
Develop Climate Adaptation Plans	develop	climat	countri	financ	sustain
Praising Corporate Sustainability	environ	sustain	üáüá	natur	green
Criticize Trump EPA	trump	epa	environ	pruitt	health

Supplementary Table 3: Emblematic Tweets

handle	text	label
c40cities	Air pollution causes longlasting harm and is a national public health crisis This new data shows that the action Im taking is already making a difference and saving lives MayorofLondon is taking action to protect residents amp improve air quality	Air Pollution
CANIntl	I urge all countries to make the Katowice Climate Conference a success and heed the counsel of the worlds top scientists raise ambition rapidly strengthen their national climate action plans and urgently accelerate implementation of the Paris Agreement COP24	Climate Action
WMO	TODAYUNSG antonioguterres speech on the State of The Planet and WMO StateofClimate report underline the need for more ClimateAction WMO report gives details on temperatures ocean heat sea level rise ice melt extreme weather etc in 2020ClimateChange ParisAgreement	Climatological Changes
foe_us	Were working for solutions to climate change For clean energy and a safe amp healthy food system To protect forests and Indigenous communitiesYour support strengthens our commitment to defend the Earth today and everyday Help us continue the fight	Corporate Sustainability
foe_us	Our environment is under threat from the pesticide industry Big Oil amp other giant corporations and Trumps administration keeps putting corporate profits ahead of people and planet Help us fight to stop Trump without spending a dime Latest reviews of developed country climate policies and actions show progress toward emission reduction targets and increased efforts to support ClimateAction in developing countries Transparency of action is a key pillar of the ParisAgreement	Criticize Trump EPA
UNFCCC		Develop Climate Adaptation Plans

foe_us	<p>HUGE WIN The UK has announced an immediate end to public finance for fossil fuel project overseasIts time for EximBankUS USTDA to follow UKs lead and stop supporting oil amp gas projects all over the world We cannot continue bankrolling the climate crisis with tax dollars</p>	Divest Fossil Fuels
NRDC	<p>Great news Under a new law passed by New Yorks city council the citys largest buildings will reduce their greenhouse gas emissions 40 by 2030 Thats a huge deal because New Yorks buildings account for a whopping 67 of the citys carbon emissions</p>	Emission Reduction
ExtinctionR	<p>Inaction How about some action on the climate and ecological emergency governmentsRebelForLife July has had extreme weather from landslides amp flooding in Japan to heatwaves from China to North America Extreme heat amp precipitation events are increasing as a result of climatechange shares the WMO See CGTVs coverage of extreme weather in Japan</p>	Extinction Rebellion
UNFCCC	<p>Climate justice is gender justiceClimate justice is racial justiceClimate justice is economic justiceClimate justice is environmental justiceGo to to join the next global climate strike and raise your voice for climate justice UprootTheSystem</p>	Extreme Weather
Greenpeace	<p>thejamestay Hi James thanks for your comments Natural gas is the smart partner to renewables as it burns 50 cleaner than coal in power generation Renewables are important but only part of the story Other sources of energy like oil amp gas will be necessary to meet growing global demand</p>	Fight Climate Change
bp_plc	<p>katiepanda ensuring our customers have a clean safe and reliable experience is one of our core values please send us a dm with the station location and your contact information email phone and we will bring this to the attention of the appropriate parties for further investigation</p>	Gas Company Advertising
Chevron		Gas Station Customer Service

Chevron	First we clearly stated our commitment to international human rights normsThis commits us to respecting human rights as set out in the United Nations Universal Declaration of Human Rights and other international human rights frameworks <a href="#">httpstco5pu9r9VaDR</a>	Indigenous Rights
bp_plc	With internship opportunities falling due to COVID19 were proud to be able to welcome over 250 students in the US UK amp Canada to our summer internships but with a difference Were providing an online programme to support students across the globe to develop their skills Events For Life	Industry Supports STEM
ExtinctionR	Offre d'emploi SENIOR PROCESS SAFETY ENGINEERING DESIGN ENGINEER ENG 1016 Balikpapan <a href="#">httptinyurlcom323kysx</a> jobs	IPCC
TotalEnergies	Today C40 mayors amp union leaders from around the world gathered to discuss the role of local national amp international leaders in scaling global ambition on climate action and a just amp green transition towards inclusive economies Stay tuned for exciting news tomorrow	Job Offers
c40cities	Starting tomorrow were launching a series of facebook live chats to shed light on the concept of Talanoa4ambition Check out todays teaser interview You can join the chats by posting your questions on our Facebook page	Mayors' Actions- City Policy
UNFCCC	Many Americans will visit coastal national parks this summer But a report by NRDC and the NPCA shows that if the Trump admin follows through on their offshore drilling plans 68 coastal national parks could be at risk of an oil spill Take action	Media Engagement
NRDC		Oppose Trump Drilling Policies



JuliesBicycle	Next ROCKH2020 Webinar Cultural Policy Driving Environmental Change i5th Sept Explore role of cultural professionals in cities sustainable development how cultural policy organisational amp local government drives environmental leadership	Praising Corporate Sustainability
ClimateGroup	The official Climate Week NYC 2020 events program is now live For the first time ever Climate Week NYC now includes virtual events from all over the world and weve invited a global audience Climate-WeekNY	Promoting Company Website
UNEP	Forests provide vital functions including as guardians of fresh water sources amp biodiversity protectionUN report progress in protecting the worlds forests is at risk due to the devastating impacts of the COVID19 pandemic amp the planetary crises	Protect Biodiversity
ClimateGroup	Since 2012 Orsted has helped reduce the levelized cost of electricity from offshore wind by more than 60 meaning it is now cheaper to build amp operate offshore wind farms in Europe than new power plants running on coal gas or nuclear Climate-WeekNYC	Renewables
EU_ENV	To celebrate the 50th anniversary of EarthDay WWF invites you to create nature themed artwork amp share with ArtForEarthDay 1 Wildlife Day 2 Freshwater Day 3 One Planet Day 4 Food Day 5 Forests Day 6 Climate Day 7 Ocean Our symbolic choice today 12	Share Pictures of Environment
foe_us	We cant continue to let pesticide companies poison our Earth kill bees at unprecedented rates amp destroy our food systemNY Its time to pass bradhoylmans Birds amp Bees Protection Act to ban beekilling neonic pesticides Take action to SaveThe-Bees	Stop toxic/plastic waste
350	8200 people have already signed the PromiseToProtect a commitment to join a wave of peaceful resistance along the route of Keystone XL when called upon by local leaders People power gt dirty pipelines Keystone XL will never be built NoKXL	Stop XL Pipeline

ClimateGroup	Across the world women are acting on climate change IWD2020We recognise that urgent action is needed now to address the global climate emergency strathearnrose Cabinet Secretary for Environment Climate Change and Land Reform ScotGov Under2Coalition	Tackle Climate Change
bp_plc	DoreMartin Hi Martin thanks for your comments We are committed to playing our part in helping the world transition to a low carbon future amp our strategy includes a framework for reducing emissions in our operations improving our products amp creating low carbon businesses	Twitter Engagement

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Supplementary Table 4: Stock Market Returns Data

Mean	St.dev	Min	Q25	Median	Q75	Max
-0.04	2.03	-17.86	-0.93	-0.001	0.82	16.77

## Supplementary Section 3 Time Series Analysis

### Supplementary Section 3.1 Overview of the Dynamic Nature of These Data

For our specification, fix a sentiment-topic label  $k$  and group  $j$ . Let  $x_{group_j,t}^k$ ,  $x_{group-j,t}^k$ , and  $s_t$  denote the probability of the average IGO/NGO/fossil fuel firm, then average of all other groups, and then average daily stock returns, respectively. Let  $X_t = (x_{group_j,t}^k, x_{group-j,t}^k, s_t)$  for all  $k$ . Then let

$$Z = \log \left( \frac{X}{1 - X} \right)$$

Our specification thus is:

$$Z_t = c + \sum_{p=t-1}^5 \beta_p Z_p + Y + \epsilon_p \quad (1)$$

where  $c$  is a constant because the time series is stationary around a non-zero mean after taking logs, we use a time lag of 5 and  $Y$  are weather controls. We then run this regression for all 30 sentiment-topics identified by our JST model. We find that across the VAR regressions, the average of the optimal number of lags selected by a Bayesian Information Criterion (BIC) average at 5. This reflects the notion that discussions on social media are often ephemeral. In our case, this corresponds to discussion effects on social media lasting generally for only a business week.

Following [1], we employ generalized impulse-response functions (IRFs) that are invariant to variable ordering (see Supplementary Section 3.4 for details). Computing confidence intervals for IRFs is analytically intractable, as they are functions of both the model coefficients and the model variance-covariance matrix. To overcome this problem, we bootstrap the full sampling distribution for the IRFs. We resample the dataset 500 times and re-fit the VAR on the resampled data to derive the sampling distribution for the IRFs. This accounts for sampling uncertainty in both the VAR coefficient estimates and the estimates for the VAR variance-covariance matrix. Because we account for these underlying sources of uncertainty when reporting the confidence intervals for the IRF results, we believe the reported IRF confidence intervals are generally conservative. Finally, we rescale the responding variables' impulse responses (which are given as changes in log odds) to changes in probability, assuming the base rate of the response is the empirical probability observed in the data. For an  $n$  step-ahead response, we compute

$$\Theta_i^k(n) = \frac{\delta_j}{\sigma_j^2} \Sigma_{\epsilon} \beta$$

where  $\delta$  is the size of the shock and set to  $\sigma$ , which is standard practice. The interpretation for this choice of delta is the predicted response for a hypothetical standard deviation increase in the impulse variable, which given the volatile nature of social media communications, is an appropriate counterfactual case to analyze; such standard deviation increases are common in the online discussion space.

Supplementary Table 5 provides summary statistics for the daily propensity of Industry's Twitter activity on the primary topics in the analysis. Similarly, Supplementary Table 6 shows similar summary statistics for the IGO topic time series, with Supplementary Table 7 showing the summary statistics for the NGO topic time series.

Supplementary Table 5: Daily Propensity: Industry

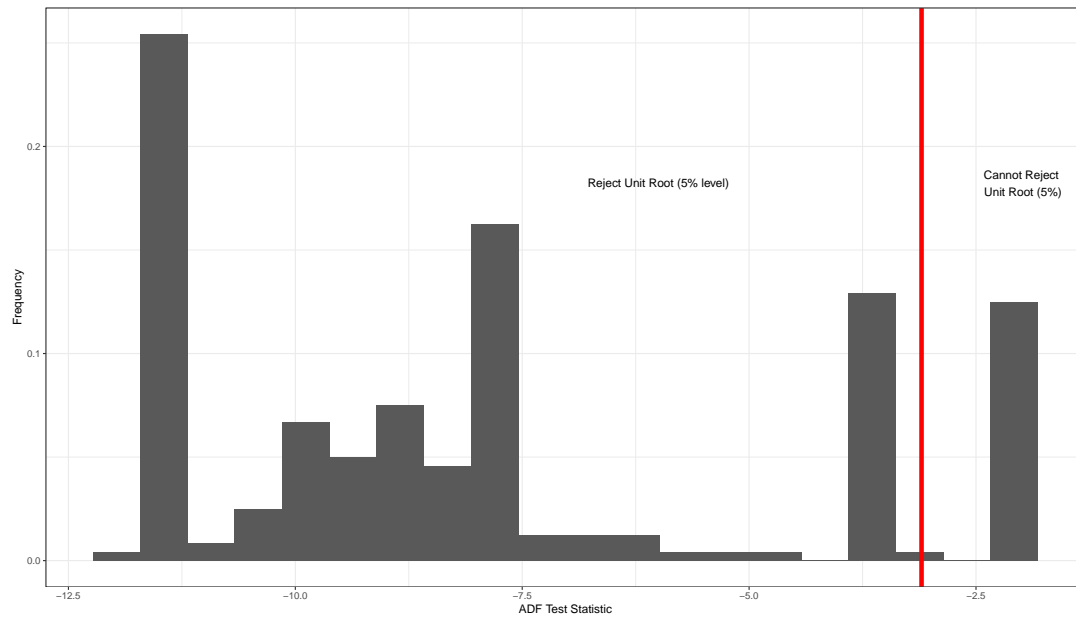
Topic	Max	Mean	Median	Min	Q25	Q75	St.dev
Air Pollution	90.19	4.40	3.57	0.06	2.14	5.47	4.36
Climate Action	53.66	8.66	8.03	0.09	6.43	10.00	4.64
Climatological Changes	78.33	8.52	7.84	0.08	6.27	10.00	4.80
Corporate Sustainability	98.79	6.64	4.66	0.09	2.65	8.56	7.86
Criticize Trump EPA	63.46	8.40	7.81	0.08	6.32	10.00	4.23
Develop Climate Adaptation Plans	98.45	10.14	8.68	0.09	6.84	11.24	7.21
Divest Fossil Fuels	94.81	8.62	7.93	0.08	6.37	10.00	4.87
Emission Reduction	98.45	11.75	9.44	0.09	7.28	13.37	9.31
Extinction Rebellion	90.19	8.31	7.76	0.08	6.27	10.00	4.44
Extreme Weather	96.47	9.01	8.04	0.08	6.45	10.00	6.01
Fight Climate Change	97.85	8.36	7.77	0.09	6.19	10.00	5.12
Gas Company Advertising	98.91	25.10	22.79	0.09	12.31	33.83	18.05
Gas Station Customer Service	99.29	22.20	18.69	0.22	10.00	28.83	15.86
Indigenous Rights	96.47	4.88	3.75	0.06	2.22	5.70	5.60
Industry Supports STEM	98.91	23.56	21.07	0.06	11.47	32.18	17.24
IPCC	96.47	8.92	8.07	0.09	6.37	10.00	5.92
Job Offers	57.75	8.12	7.67	0.09	6.07	10.00	3.97
Mayors' Actions- City Policy	96.47	8.83	8.04	0.09	6.40	10.00	5.78
Media Engagement	99.16	13.58	10.00	0.09	7.74	16.06	10.71
Oppose Trump Drilling Policies	97.33	9.20	8.12	0.08	6.44	10.00	6.40
Praising Corporate Sustainability	97.33	5.68	4.19	0.06	2.41	7.22	6.36
Promoting Company Website	99.09	10.03	6.72	0.06	3.45	12.44	12.14
Protect Biodiversity	97.33	5.17	3.94	0.06	2.28	6.30	5.61
Protect Endangered Species	94.81	8.43	7.80	0.08	6.28	10.00	4.71
Renewables	99.09	7.48	5.15	0.06	2.84	9.65	8.57
Share Pictures of Environment	98.64	7.06	4.89	0.06	2.66	8.71	8.70
Stop toxic/plastic waste	98.03	8.86	8.05	0.08	6.41	10.00	5.35
Stop XL Pipeline	96.47	8.46	7.79	0.08	6.28	10.00	5.25
Tackle Climate Change	98.45	8.46	7.89	0.09	6.33	10.00	5.19
Twitter Engagement	99.16	13.18	10.00	0.09	7.77	15.74	9.83

Supplementary Table 6: Daily Propensity: IGOs

Topic	Max	Mean	Median	Min	Q25	Q75	St.dev
Air Pollution	39.12	7.27	6.32	0.11	4.30	9.23	4.42
Climate Action	90.19	12.60	11.21	0.15	7.56	15.82	6.91
Climatological Changes	54.10	13.08	12.05	0.17	8.47	16.15	6.01
Corporate Sustainability	64.95	12.60	11.19	0.13	7.51	15.83	7.67
Criticize Trump EPA	28.33	8.00	7.49	0.17	6.35	9.19	2.66
Develop Climate Adaptation Plans	98.64	16.72	15.59	0.20	11.20	20.83	8.20
Divest Fossil Fuels	57.07	7.91	7.38	0.17	6.26	8.87	2.96
Emission Reduction	53.93	9.04	7.86	0.15	5.88	11.17	4.69
Extinction Rebellion	35.85	8.18	7.57	0.17	6.37	9.40	2.90
Extreme Weather	64.45	13.79	12.66	0.17	9.04	17.07	6.43
Fight Climate Change	45.20	7.81	6.80	0.15	5.23	9.54	3.97
Gas Company Advertising	53.24	6.01	5.24	0.10	3.82	7.59	3.54
Gas Station Customer Service	96.47	7.72	7.32	0.17	6.21	8.56	3.02
Indigenous Rights	42.03	6.38	5.52	0.10	4.03	8.11	3.71
Industry Supports STEM	50.10	6.73	5.90	0.10	4.09	8.63	3.91
IPCC	98.20	14.18	12.13	0.15	7.90	17.43	9.04
Job Offers	38.82	5.89	5.63	0.15	4.54	6.79	2.39
Mayors' Actions- City Policy	48.81	8.46	7.43	0.15	5.62	10.43	4.19
Media Engagement	53.24	8.60	7.59	0.15	5.69	10.45	4.38
Oppose Trump Drilling Policies	98.45	8.01	7.44	0.24	6.31	8.98	3.57
Praising Corporate Sustainability	98.20	14.37	12.96	0.10	8.85	18.48	8.29
Promoting Company Website	96.47	8.90	7.70	0.10	4.51	11.51	6.45
Protect Biodiversity	98.79	20.46	19.15	0.11	13.10	25.97	10.48
Protect Endangered Species	97.85	14.00	12.57	0.17	9.30	17.18	6.98
Renewables	51.72	7.93	6.86	0.10	4.33	10.09	5.22
Share Pictures of Environment	97.77	9.35	8.23	0.10	5.09	11.86	6.71
Stop toxic/plastic waste	90.19	11.68	10.51	0.17	7.85	14.02	5.59
Stop XL Pipeline	50.10	7.63	7.25	0.17	6.17	8.51	2.61
Tackle Climate Change	37.45	8.87	7.92	0.15	5.87	10.88	4.31
Twitter Engagement	53.93	7.83	6.86	0.15	5.26	9.65	3.82

Supplementary Table 7: Daily Propensity: NGOs

Topic	Max	Mean	Median	Min	Q25	Q75	St.dev
Air Pollution	42.48	12.18	11.56	2.87	9.39	14.17	4.22
Climate Action	41.41	10.74	10.01	3.38	8.13	12.33	4.01
Climatological Changes	31.34	9.31	8.67	1.73	6.77	11.27	3.65
Corporate Sustainability	39.00	11.01	9.83	2.23	8.10	12.55	4.74
Criticize Trump EPA	66.33	12.36	10.53	2.57	7.85	15.08	6.79
Develop Climate Adaptation Plans	26.09	8.79	8.47	2.14	7.20	10.09	2.42
Divest Fossil Fuels	30.44	10.82	10.10	2.32	7.87	13.08	4.23
Emission Reduction	24.98	9.06	8.77	2.64	7.28	10.42	2.62
Extinction Rebellion	58.64	10.27	7.89	2.02	6.03	10.72	7.48
Extreme Weather	29.73	9.15	8.66	2.00	6.69	11.00	3.53
Fight Climate Change	55.24	13.52	11.95	2.63	9.29	16.47	5.98
Gas Company Advertising	22.58	7.95	7.73	1.61	6.50	9.18	2.16
Gas Station Customer Service	24.28	5.73	5.57	1.48	4.56	6.67	1.71
Indigenous Rights	43.39	12.22	11.68	3.13	9.54	14.40	3.91
Industry Supports STEM	17.37	7.66	7.48	2.27	6.28	8.82	2.02
IPCC	46.52	7.77	7.49	2.32	6.34	8.81	2.39
Job Offers	19.98	6.45	6.40	1.17	5.52	7.23	1.55
Mayors' Actions- City Policy	46.19	11.17	10.43	2.91	8.27	13.13	4.24
Media Engagement	44.53	8.67	8.19	1.90	6.92	9.79	2.87
Oppose Trump Drilling Policies	38.92	11.32	10.41	2.32	8.38	13.34	4.38
Praising Corporate Sustainability	33.22	8.91	8.64	2.39	7.07	10.39	2.67
Promoting Company Website	28.24	7.54	7.35	2.23	6.07	8.75	2.16
Protect Biodiversity	25.14	8.45	8.23	1.61	6.83	9.70	2.45
Protect Endangered Species	30.86	9.39	8.86	2.23	7.12	11.04	3.44
Renewables	36.70	13.20	12.52	2.27	9.20	16.55	5.36
Share Pictures of Environment	49.73	10.86	10.32	2.99	8.51	12.58	3.69
Stop toxic/plastic waste	36.16	11.80	11.08	2.06	8.93	14.02	4.23
Stop XL Pipeline	64.11	9.84	8.74	1.48	6.58	11.57	5.37
Tackle Climate Change	32.88	12.80	12.45	3.40	10.18	14.93	3.80
Twitter Engagement	43.65	11.03	10.68	2.84	8.55	12.90	3.61



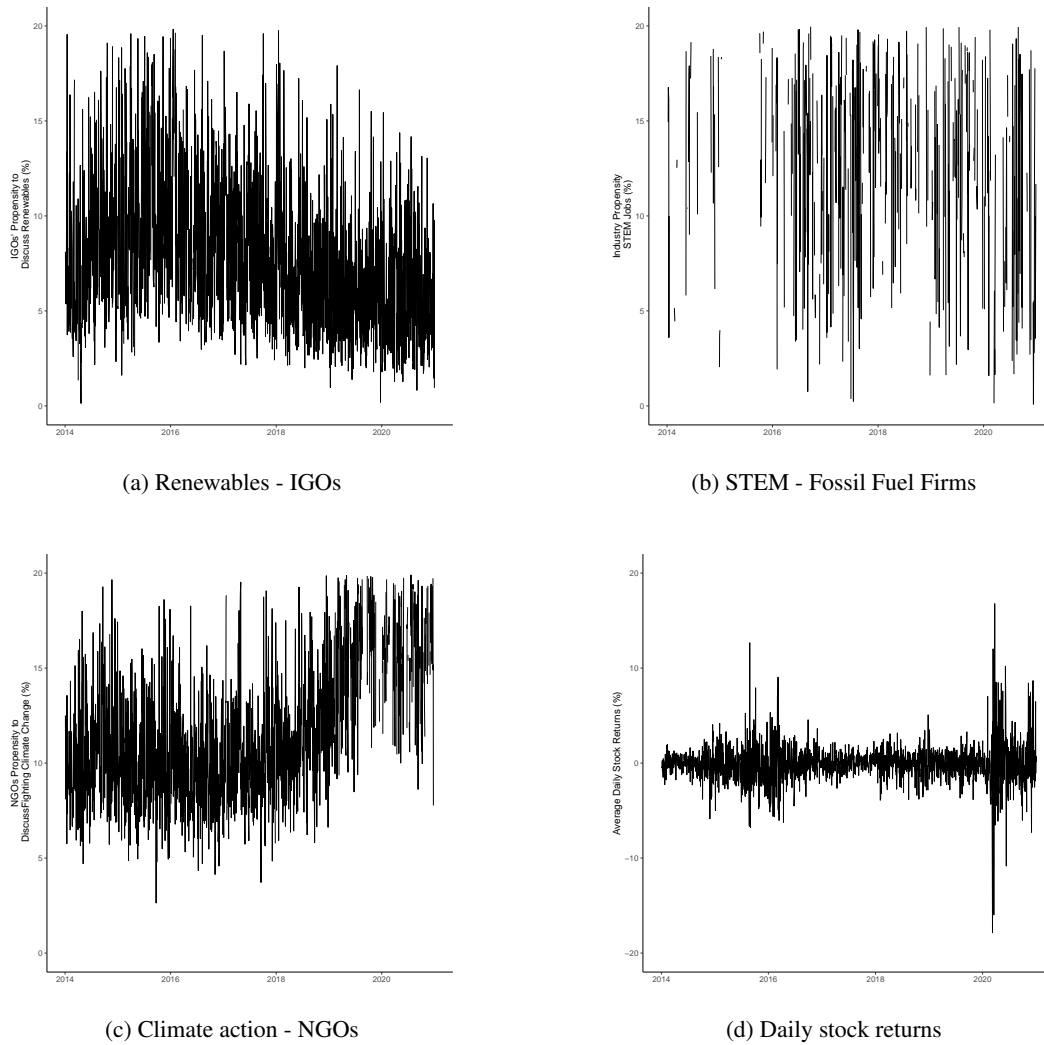
Supplementary Figure 3: Augmented Dickey-Fuller Tests for Unit Root with Trend

### Supplementary Section 3.2 Stationarity

Augmented Dickey-Fuller (ADF) test is a common statistical significance test used to test whether a given time series is stationary or not based on the presence of a unit root. The presence of a unit root means the time series is non-stationary. In Supplementary Figure 3, we provide a histogram of ADF test statistics, indicating the distribution of topics for which we reject the null of a unit root at the one percent level or at 99% significance level.

### Supplementary Section 3.3 Vector Autoregression Analysis

In Supplementary Figure 4 we provide four times series of some of the more interesting components of our VAR analysis. The remainder of these time series graphs will be available upon publication.



Supplementary Figure 4: Daily Propensity of Discussion



### Supplementary Section 3.4 Impulse Response Function Estimation

In order to estimate the impulse response functions, we closely follow [1] and implement a version of generalized impulse response functions. Our implementation uses a modified version of the `VAR` and `irf` functions from the `vars` package in R. For details on the `vars` package used to implement the time series analysis in R, please refer to [4] and [5].

We slightly modify the IRF function implemented in [5] to accommodate the generalized approach implemented in [1]. This allows for analysis of coefficients that are invariant to variable ordering. As is well known in the time-series econometric literature, IRFs are potentially sensitive to the ordering in which you analyze the variables. As we wish to compare effects across variables, we use generalized IRFs, where the results do not change depending on how one orders the variables.

To achieve this, the generalized impulse response appropriately accounts for the effects of a non-diagonal variance-covariance matrix on a potential impulse response, ie. the case when there is a estimable covariance structure in the data. Of course, it reduces to a standard IRF in the case when the off-diagonal elements of the variance-covariance matrix are 0. Unlike the orthogonalized impulse response, [1] note that the generalised IRF is unique.

The generalized impulse response we calculate is

$$GIRF = \frac{1}{\sqrt{\sigma_{ii}}} A_n \eta_i$$

where  $\sigma_{ii}$  is the variance of the  $i$ th variable,  $A_n$  is the matrix of model coefficients, and  $\eta_i$  is the vector of covariances for the  $i$ th variable with all other variables.

### Supplementary Reference

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