### **Supplementary Material**

Supporting materials include Tables 1-5 and References at the end.

Data Type Number of Policymakers Number of Tweets or			
Number of Policymakers	Number of Tweets or Meeting Transcripts		
	meeting manseripts		
.39	70,391		
	,		
.39	2593		
95	661		
.40			
	Sumber of Policymakers		

### Table 1. Summary of Data Types Collected for Policymakers in Treatment Group (N = 140).

### Table 2. Summary of Data Types Collected for Policymakers in Control Group (N = 140).

Data Type	Number of Policymakers	Sample Size of Texts (ie tweets)
Tweets (3-months pre to post intervention of matched treated policymaker)	116	31,380
Climate change-related Tweets (3-months pre to post intervention)	116	736
Sociodemographic and Constituency Information	140	

## Table 3. Results from Independent Samples T-tests Comparing Pre- to Post-Intervention Sentiment Measures of Climate-related Tweets (N=2593) from Treatment Group (N=139).

Measure	Pre Mean	Post Mean	p-value
Frequency of cc-related <sup>1</sup> tweets	0.031	0.0267	>0.05
Analytic Terms (terms related to logical and formal thinking)	74.0	77.0	0.0007**
Politics-related Terms (i.e., united states, congress, senate)	1.9	2.4	<0.0001***
Money-related Terms (i.e., business, pay, price, market)	1.1	1.5	<0.0001***
Reward Motive Terms (i.e., opportunity, win, gain, benefit)	0.16	0.26	0.002**
Insight-oriented Terms (i.e., know, how, think, feel)	1.6	1.6	>0.05
Emotional Tone (i.e., higher value means more positive tone)	27.8	29.4	>0.05
Future-oriented Terms	1.6	1.4	>0.05

<sup>1</sup>Note that 'cc-related' refers to climate change-related.

Variable / Value Types	Model 1	Model 2
Intercept		
Beta Parameter Estimate (B0)	0.0213	0.0286
Standard Error	0.00368	0.00408
p-value	<0.001***	<0.001***
Treat – Treatment Group (B1)		
Beta Parameter Estimate	0.0109	0.0101
Standard Error	0.004	0.00484
p-value	0.0287*	0.038*
Post – Post-intervention (B2)		
Beta Parameter Estimate	0.00120	0.00116
Standard Error	0.00520	0.00506
p-value	0.818	0.819
Treat:Post – DID Interaction Variable (B3)		
(post-intervention tweets in treatment group)		
Beta Parameter Estimate	-0.00480	-0.00473
Standard Error	0.00702	0.00684
p-value	0.495	0.490
Is_Female (B4)		
Beta Parameter Estimate		-0.00257
Standard Error		0.00385
p-value		0.505
Is_Republican (B5)		
Beta Parameter Estimate		-0.0225
Standard Error		0.00410
p-value		<0.001***
ls_NonWhite (B6)		
Beta Parameter Estimate		-0.0073
Standard Error		0.00684
p-value Global Model		0.545
Posidual Standard Error	0 0202 on 502 DE	0 02827 on 400 DE
	0.0090 011 002 DF	0.03027 011 499 DF
F-statistic	2 167 on 3 and 502 DE	0.00000 6 261 on 6 and 100 DE
n-value	0.091	< 0.001***

Table 4. Comparison of Results from Two Diff-in-Diff Linear Regression Models Estimating Effect ofIntervention Treatment on Climate-related Tweet Rate, with Model 1 Including No OtherIndependent Variables and Model 2 Including Binary Variables for Gender, Party, and Race.

# Table 5. Sample of Climate Change-related Tweets with High Analytic Tone and Tweets withHigh Reward-motivated Terms.

Text	Analytic	Reward- motivated	Emotional Tone
From committing to 100 percent renewable energy, to embracing a carbon neutral economy, Hawaii has taken aggressive action to combat climate change because of the threat it poses to our way of life.	99	0	1
The process of withdrawing from the Paris climate agreement begins today. The process of returning begins on election day next year.	99	0	1
The transportation sector accounts for nearly 30% of the carbon emissions. Electric vehicles are of critical importance for reduction of greenhouse gases. The US cannot afford to get behind in innovation and technology.	99	0	20.23
Grateful for this opportunity to see firsthand the opportunities we have to protect #Florida and the rest of our beautiful country through our work at the Select Committee on the @ClimateCrisis.	98.94	5.56	99
Climate change is intensifying inequality, but fighting it is an historic opportunity to deliver economic justice for all, especially the most vulnerable. Creating a truly healthy, livable planet requires commitment to both goals. They are inseparable.	81.21	4.88	58.42
With this training infrastructure, students + trade workers will gain the skills and knowledge necessary to be a part of the growing sector of Massachusetts' nation-leading clean energy industry and can take advantage of the highly- skilled jobs created by this emerging industry.	95.99	4.35	20.23

#### <u>References</u>

- Milfont, T.L., Zubielevitch, E., Milojev, P., Sibley, C.G., 2021. *Ten-year panel data confirm generation gap but climate beliefs increase at similar rates across ages*. Nature Communications 12, 4038.
- Callaghan, M., Schleussner, C.-F., Nath, S., Lejeune, Q., Knutson, T.R., Reichstein, M., Hansen, G.,
  Theokritoff, E., Andrijevic, M., Brecha, R.J., Hegarty, M., Jones, C., Lee, K., Lucas, A., van Maanen,
  N., Menke, I., Pfleiderer, P., Yesil, B., Minx, J.C., 2021. *Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies*. Nature Climate Change.
- IPCC, 2022. Summary for Policymakers, in: Pörtner, H.-O., Roberts, D.C., Poloczanska, E.S., Mintenbeck, K., Tignor, M., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. (Eds.), Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK
- Leiserowitz, A., Maibach, E., Rosenthal, S., Kotcher, J., Carman, J., Lee, S., Verner, M., Ballew, M., Ansah,
  P., Badullovich, N., Myers, T., Goldberg, M., & Marlon, J. (2023). *Climate Change in the American Mind: Politics & Policy*, December 2022. Yale University and George Mason University. New
  Haven, CT: Yale Program on Climate Change Communication.
- Chinn, S., Hart, P. S., & Soroka, S. (2020). Politicization and polarization in climate change news content, 1985-2017. *Science Communication*, *42*(1), 112-129.
- Flores, R. D. (2017). Do anti-immigrant laws shape public sentiment? A study of Arizona's SB 1070 using Twitter data. *American Journal of Sociology*, *123*(2), 333-384.
- Choi, Y., & Kim, S. U. (2022). A longitudinal comparison of public libraries' posting activities on Twitter in April of 3 years, pre-, during, and post-COVID-19. *Journal of Librarianship and Information Science*, 09610006221128981.
- Effrosynidis, D., Karasakalidis, A. I., Sylaios, G., & Arampatzis, A. (2022). The climate change Twitter dataset. *Expert Systems with Applications*, *204*, 117541.
- Gunaratne, K., Coomes, E. A., & Haghbayan, H. (2019). Temporal trends in anti-vaccine discourse on Twitter. *Vaccine*, *37*(35), 4867-4871.
- Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: best practices for public health policy research. *Annual review of public health*, *39*.
- Costain, A. N., & Majstorovic, S. (1994). Congress, social movements and public opinion: multiple origins of women's rights legislation. *Political Research Quarterly*, 47(1), 111-135.
- Boyd, R. L., Ashokkumar, A., Seraj, S., & Pennebaker, J. W. (2022). The development and psychometric properties of LIWC-22. *Austin, TX: University of Texas at Austin,* 1-47.