# Intra-Party Variation on Climate Change Positions in U.S. House Elections

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**Abstract**

Previous research documents partisan polarization on climate change in the United States extensively. However, little is known about intra-party variation in politicians' positions on climate change. Using a word embeddings approach, we assess the relationship between position-taking on climate change and climate-relevant factors in congressional districts. We train our embeddings on a corpus of campaign platforms from U.S. House of Representatives candidates who ran between 2018 and 2022. We demonstrate that Republicans attribute extreme weather events to climate change more closely in districts with heightened climate-related disaster risk. We also demonstrate that Republicans support renewable energy investment conditional on district-level fossil fuel reliance. Democrats display remarkable consistency in their position-taking across all district-level factors. Our findings shed light on potential pro-climate congressional coalitions that might be formed in the future.

**Keywords**: Climate Change, Text-as-Data, Polarization, U.S. Elections

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Climate change poses substantial, escalating risks to economic, political, and social systems over the medium and long term. Scientists estimate that each additional degree Celsius in warming above pre-industrial levels will cause over $1 trillion in cumulative damages in the United States by 2100 (Hsiang et al., 2017). Addressing climate change in the United States requires (1) the attribution of extreme weather to rising temperatures by political elites and (2) policy support for decarbonizing the energy sector through renewable electricity production (IPCC, 2023). These positions enjoy widespread support among Democrats in the U.S. Congress, but Republican politicians generally oppose climate policy action (e.g., Guber et al. 2021; Egan and Mullin 2023). As a result, legislative responses to the causes and consequences of climate change remain largely gridlocked. Reducing partisan polarization on climate policy, therefore, requires a significant shift in Republican politicians' positions on climate change attribution and renewable energy investment (Brulle et al., 2012; Benegal and Scruggs, 2018).

Politicians have many electoral and legislative incentives to toe the party line on policy (e.g., Ansolabehere and Iyengar 1994; Pearson 2015). Yet, politicians are also risk-averse (Rohde, 1979) and sensitive to district-level considerations (Fenno, 1978). Existing research demonstrates that politicians face potential electoral losses when they neglect salient problems in their district or fall out of step with constituents' preferences (e.g., Canes-Wrone et al. 2002; Grose and Oppenheimer 2007; Porter 2022). This suggests that both partisanship *and* local conditions shape politicians' position-taking behavior. In this vein, some scholars suggest that Republican politicians may adopt more pro-climate policy stances in response to climate-relevant conditions in their own constituencies (e.g., Coley and Hess 2012; Egan and Mullin 2023). These theories align with previous research documenting substantial variation in the climate change attitudes of Republican voters (e.g., Mildenberger et al. 2017; Marlon et al. 2022). To our knowledge, however, few studies empirically evaluate whether Republican politicians deviate from their party's position on climate change. Our paper contributes to the literature on climate policy within American politics by assessing the relationship between climate-relevant factors at the congressional district level and politicians' positions on climate change attribution and renewable energy investment.

We expect that Republicans link extreme weather events to climate change more closely in districts with heightened climate-related disaster risk. Several findings from previous research underpin this expectation. Republican politicians may attribute extreme weather to climate change in vulnerable districts because pro-climate candidates tend to perform better at the polls in these areas (Herrnstadt and Muehlegger, 2014; Liao and Junco, 2022). Alternatively, Republican politicians may adopt an anticipatory representation style in districts with heightened risk because they predict future negative consequences if they fail to discuss climate change accurately in the present (Mansbridge, 2003). In either case, though, Republicans may have incentives in these districts to buck their party and attribute extreme weather to rising temperatures.

We also expect an association between Republicans' advocacy for renewable energy investment and their districts' reliance on fossil energy production. Previous research shows that the decarbonization of electricity capacity and generation has substantial socioeconomic costs for fossil fuel-reliant communities (Raimi et al., 2022). In these kinds of districts, politicians' support of renewable energy investment can lead to considerable electoral backlash (Stokes, 2016). On the other hand, Republicans from communities with limited fossil fuel reliance may see renewable energy investment as an opportunity to bolster, and subsequently claim credit for, local economic gains (Mayhew, 1974; Cassella et al., 2023). As such, we expect Republican politicians from districts with low (high) reliance on fossil energy production to more (less) closely associate renewable energy with policy investments.

To evaluate politicians' positions on climate change, we analyze a corpus of campaign platforms of congressional candidates who ran for the U.S. House between 2018 and 2022. We pair these texts with a method that places à la carte word embeddings within a multivariate regression framework (Khodak et al., 2018; Rodriguez et al., 2023). This approach allows us to evaluate the use of words in context and track how contextual word usage shifts with district-level covariates. We find that Republicans more closely associate climate change with extreme weather as their districts' climate-related disaster risk increases, but that their climate change attribution remains significantly lower than Democrats'. We also show that, for districts with low fossil fuel reliance, Democrats and Republicans are statistically indistinguishable in their support for renewable energy investment. However, as fossil fuel reliance increases, the association between renewable energy and policy investments declines precipitously among Republicans, while remaining consistent among Democrats. These findings have important implications for practical efforts to address the climate crisis. Given that passing major legislative enactments almost always requires bipartisan support (Curry and Lee, 2019), these findings offer a roadmap to the kinds of pro-climate congressional coalitions that might be formed in the future.

# Data

To assess politicians' positions on climate change, we examine a corpus of policy platforms scraped from the campaign websites of U.S. House of Representatives candidates who ran in 2018, 2020 or 2022.[1] We examine congressional campaign content for several reasons. First, policy discussions related to climate change are generally infrequent in Congress and are especially rare among Republicans.[2] In contrast, climate policy discussions in elections provide a large and diverse sample of observations across congressional districts with varying levels of climate-related disaster risk and fossil fuel reliance. Second, understanding how politicians communicate about climate policy on the campaign trail is substantively important. Concern for climate change is partially driven by elite cues (Brulle et al., 2012), and electoral campaigns are one of the primary venues that elites use to communicate their policy stances to broad audiences (Sulkin, 2005). We analyze policy platforms from campaign websites in particular because, unlike other sources of political text (e.g., social media posts or floor speeches), these documents are expressly policy-oriented.[3] Furthermore, campaign websites are an unmediated form of communication that provides a complete inventory of issues that candidates consider important to their campaigns (Druckman et al., 2009a). Candidates face no time or space restrictions on their campaign websites, allowing them

[1] See Appendix Section for a thorough discussion of this data source and our collection strategy.

[2] In Gruber et al.'s (2021) analysis of one-minute speeches from the *Congressional Record*, the authors find that over 30% of all speeches about climate change since 2012 came from a single speaker. In Wynes et al.'s (2022) analysis of U.S. House members' social media, just 28% of Republicans tweeted about climate change at least once.

[3] Russell (2021) finds that policy content only constitutes a fraction of politicians' Twitter posts. Harris (2005) shows that party-orchestrated message campaigns account for one-third of speeches in the *Congressional Record*.

to emphasize every issue they view as important to voters. Finally, because candidates control the contents of their policy platforms directly, these texts may better reflect their stances on policy than other forms of revealed preferences, such as roll call votes (Snyder Jr. and Groseclose, 2000; Cox and McCubbins, 2005).

A wide body of literature finds that strategic candidates tailor their policy positions to their electoral context, while "hopeless" politicians are less responsive to such conditions and run for other reasons—not necessarily to win (e.g., Jacobson 1989). We are interested in how strategic office seekers tailor their position-taking to district-level conditions and, therefore constrain our analyses to "serious" candidates. Following recent work (e.g., Thomsen 2022; Porter et al. 2024), we consider candidates to be "serious" if they raised at least $75,000 in campaign receipts from individual contributors during their campaign.[4] Of the 6,006 major party U.S. House candidates who ran between 2018 and 2022, a total of 2,628 (44%) fit our criteria for inclusion. In Appendix Section B.2 we provide descriptive information about candidates' discussions of climate change in their campaign platforms.

## Climate-Related Disaster Risk

We expect Republicans to attribute extreme weather events to climate change more closely when the costs of climate-related disasters rise. The main independent variable in our analysis of climate change attribution is a measure of district-level expected annual losses (EAL) from climate-related disasters in 2020 dollars, based on the U.S. Federal Emergency Management Agency's National Risk Index (NRI).[5] This measure quantifies census tract-year-wise EAL based on the average loss of buildings, population, and agriculture due to a variety of natural hazards (e.g., hurricanes, heat waves, and wildfires).[6] We employ this measure in particular because it accounts for both hazard frequency and severity. Furthermore, EAL focuses on historic losses rather than projected future costs. Existing research finds that immediate, not necessarily future, risk may trigger pro-climate

[4]See Appendix Section B for more discussion and descriptives about our selection criteria.

[5]See Appendix Section C.1. for a discussion of FEMA's National Risk Index and EAL measure.

[6]Calculations of EAL do not explicitly account for climate change and include two climate-unrelated hazards (i.e., earthquakes and volcanic activity). We recalculate EAL without these hazards and use this measure in all analyses.

action among Republican politicians (Gagliarducci et al., 2019). Finally, EAL is available at the census tract-level, allowing for a more fine-grained analysis of district-level extreme weather than is possible with state-level data. To transform census tract-level EAL estimates into district-level estimates, we employ areal weighted interpolation. For detail regarding our approach and necessary methodological assumptions, see Appendix Section C.1.

## Fossil Fuel Reliance

We expect Republicans to associate renewable energy with policy investments less (more) closely when their district relies more (less) heavily on fossil fuels. The main independent variable in our analysis of renewable energy investment is a district-level measure of fossil fuel reliance. To create this measure, we use data on power plant activity from the U.S. Energy Information Administration.[7] We geolocate operational power plants into congressional districts using year-appropriate boundaries and compute the total megawatt generation for fossil fuel sources of energy (i.e., coal, oil, and gas) across all plants in each district.

## Public Opinion

To contextualize our findings, we also assess the relationship between elite position-taking and climate change public opinion using data from the Yale Program on Climate Change Communication (Howe et al., 2015; Marlon et al., 2022).[8] For our climate attribution analysis, we examine whether candidates associate extreme weather events with climate change more closely when their constituents believe that global warming affects U.S. weather. For our renewable energy analysis, we examine whether candidates associate renewable energy with policy investments more closely when their constituents support federal funding for renewable energy research. Because longitudinal data are only available at the county-level, we again rely on weighted areal interpolation to construct district-level estimates.[9]

[7] See Appendix Section C.2 for more details on this data source and our data cleaning procedure.

[8] See Appendix Section C.3 for exact survey question wording and greater detail on these data.

[9] We compare our interpolated estimates of public opinion with district-level estimates released by Marlon et al. (2022) for the 118th Congress and find they are highly correlated. See Appendix Section C.3 for a discussion.

# Method

We use a word embeddings approach to examine whether and how position-taking on climate change shifts based on district-level conditions. Unlike traditional "bag of words" approaches for computational text analysis that focus on the unordered contents of an entire document, word embedding approaches treat texts as ordered sequences of words and are designed to predict word(s) occurrences based on a narrow window of surrounding words. Resulting parameter estimates (i.e., word embeddings) are vector representations of the contextual use of word(s), and semantic similarity between words can be calculated as the distance between embeddings (Kozlowski et al., 2019). We compute the distance between word embeddings using cosine similarity, where values closer to 1 (-1) indicate greater (lesser) likelihood of co-occurrence.

Table 1 presents target phrases and keyword terms used in our analyses. We include multiple target phrases to account for potential partisan variation in semantic choices surrounding climate change and renewable energy. To select keyword terms, we relied on the authors' substantive knowledge, cross-referenced available word lists, and carefully read sample texts from our corpus. We follow extant work (e.g., Garg et al. 2018; Kitagawa and Shen-Bayh 2024) and rely on multiple keywords to capture concepts of interest, thus reducing the sensitivity of our findings to term selection. Our main results presented in Figures 1 and 2 reflect the average pairwise cosine similarity between our target phrases and keyword terms.[10] In the Appendix, we demonstrate that our results are robust to a variety of alternative target phrases (Figures E.4 and E.5) and keyword terms (Figures E.6 and E.7).

## ALC Embedding Estimation

To generate our word embeddings, we rely on a method that places à la carte (ALC) word embeddings (Khodak et al., 2018) in a statistical framework, as proposed by Rodriguez et al. (2023). This approach provides a computationally efficient way to identify how embeddings differ across district-level covariates. We generate word embeddings using the R package `conText` devel-

[10] Disaggregated results for pairwise cosine similarities are available in Appendix Figures E.2 and E.3.

Table 1: Focal Phrases and Keyword Terms for Word Embedding Analyses

| **Analysis: Climate Change Attribution** | |
|---|---|
| **Target Phrases** | **Keyword Terms** |
| `climate change; global warming` | `extreme, disasters, temperatures, weather, catastrophic` |
| **Analysis: Renewable Energy Support** | |
| **Target Phrases** | **Keyword Terms** |
| `clean energy; renewable energy` | `incentives, encourage, investment, prioritize, future` |

*Note:* For sample excepts of keywords terms in context see Appendix Table F1.

oped by Rodriguez et al. (2023) and implement the best practices proposed by Denny and Spirling (2018) for text pre-processing, as well as best practices for hyper-parameter selection proposed by Rodriguez and Spirling (2022).[11] Appendix Section D provides a full discussion of text pre-processing, modeling procedures, and robustness checks.

We estimate our models with district-level measures of climate-related disaster risk, fossil fuel reliance, and climate change public opinion. We discretize these continuous measures into deciles, and interact them with candidates' party affiliations, which allows for possible non-linear relationships and the detection of subtle changes in cosine similarities.[12] We also control for district partisanship, candidate gender, and election year in our embedding regressions.[13] We expect to observe the greatest shifts in Republican positions on climate change at the minimum and maximum values of our district-level covariates.

# Results

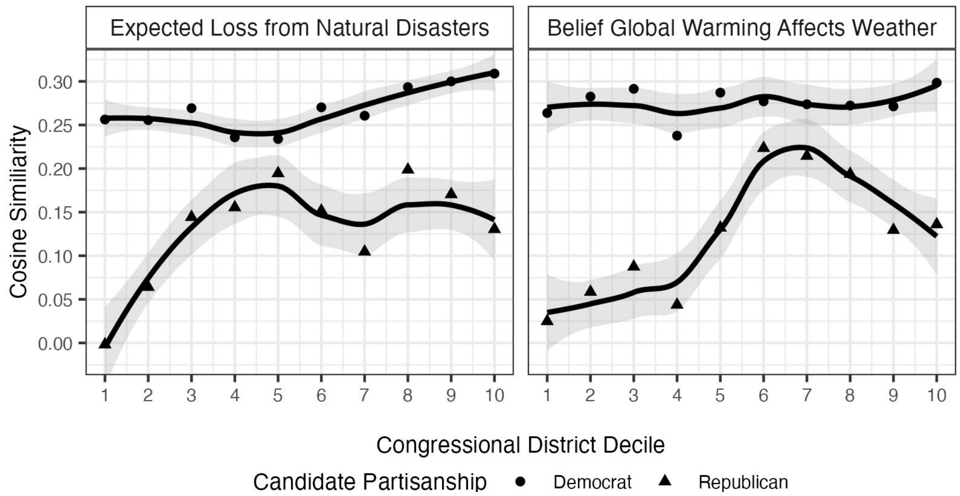
Figure 1 displays the results of our climate attribution analysis. Point estimates reflect average cosine similarities between keywords in the top row of Table 1 and predicted ALC embeddings for the target phrases `climate change` and `global warming`. Per the left panel, Democratic candidates more closely associate extreme weather events with climate change than do Republicans across the full range of district-level EAL. Republicans, however, associate climate change and

[11]Our ALC embeddings were generated with 6-word context windows and 300-dimensional vectors. We employ GloVe pre-trained embeddings and a corresponding transformation matrix.

[12]Our approach follows extant work employing ALC word embeddings (Garg et al., 2018; Kitagawa and Shen-Bayh, 2024). Results presented below are robust to various bin sizes.

[13]See Appendix Section C.4 for more discussion.

Figure 1: Average Cosine Similarity Between Climate Change Target Phrases and Extreme Weather Keywords




*Note:* Plots reflect averaged cosine similarities between target phrases and keywords from the top row of Table 1. For disaggregated results, see Appendix Figure E.2. 95% confidence intervals are bootstrapped 100 times using pre-trained GloVe vectors and ALC transformation matrix.

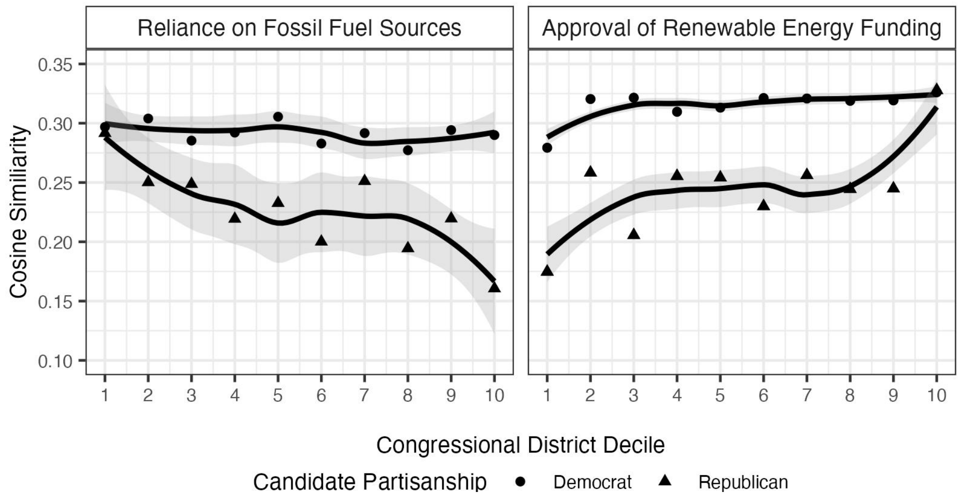
extreme weather more closely when their districts face heightened climate-related disaster risk. This increase attenuates around the median value of EAL. The magnitude of increase in cosine similarity among Republicans closely mirrors that seen in the right panel of Figure 1 when moving from low to high belief that global warming affects U.S. weather.[14]

In Appendix Figure E.1, we replicate our analysis using hazard-specific EAL and find variation in the relationship between climate attribution and hazard-specific risk. For instance, we find that Republicans increasingly associate climate change and extreme weather in districts with elevated EAL from wildfires and heatwaves but are also statistically indistinguishable from Democrats. For other hazards (e.g., hurricanes) we find a more mixed relationship between expected losses and climate change attribution.

Figure 2 displays the results of our renewable energy investment analysis. Point estimates reflect average cosine similarities between keywords in the bottom row of Table 1 and predicted ALC embeddings for the target phrases `renewable energy` and `clean energy`. Per the

[14]There is a weakly negative correlation between district climate-related disaster risk and public belief that global warming affects U.S. weather ($r$ = -0.26). The correlation between public belief and Democratic presidential vote is 0.81.

Figure 2: Average Cosine Similarity Between Renewable Energy Target Phrases and Investment Keywords




*Note:* Plots reflect averaged cosine similarities between target phrases and keywords from the bottom row of Table 1. For disaggregated results, see Appendix Figure E.3. 95% confidence intervals are bootstrapped 100 times using pre-trained GloVe vectors and ALC transformation matrix.

left panel, Democratic and Republican candidates in districts with low reliance on fossil energy production are statistically indistinguishable in their positions on renewable energy investment. However, as fossil fuel reliance increases, Republicans associate renewable energy with policy investments less closely. Democrats, on the other hand, consistently tie renewable energy to policy investments across the full range of district-level fossil fuel reliance. Again, the magnitude of decrease among Republicans tracks with the increase in cosine similarity in districts where public approval of funding for renewable energy research is high.[15]

# Discussion

The most significant implications of this work lie in understanding potential future drivers of climate policy action given partisan polarization on climate change in Congress and American politics more broadly. Further, this work provides a valuable template for scholars seeking to use word embeddings for a contextualized analysis of elite position taking. Our findings suggest that there is significant intra-party variation in Republican congressional candidates' positions on climate

[15]There is a weakly negative correlation between district-level fossil fuel energy production and public approval of renewable energy research ($r$ = -0.28). The correlation between public belief and Democratic presidential vote is 0.37.

change related to district-level climate-related disaster risk and fossil fuel reliance. This suggests that coalition-building to support climate change legislation may enjoy greater support from some parts of the Republican Party than others. A cohesive Democratic Party might find bipartisan allies in districts that may experience more frequent and severe natural hazards related to rising temperatures. Similarly, Republicans from districts with lower levels of fossil fuel reliance may be more likely to support legislation advancing clean energy policies.

# References


Agency, E. P. (2022). Climate change indicators: Heat waves. Technical report.

Algara, C. and B. Bae (2024). Do quality candidates and incumbents still matter in the partisan world? comparing trends and relationship between candidate differentials and congressional election outcomes, 1900-2022. *Journal of Political Marketing*.

Ansolabehere, S. and S. Iyengar (1994). Riding the wave and claiming ownership over issues: The joint effects of advertising and news coverage in campaigns. *Public Opinion Quarterly 58*(3), 335–357.

Association, F. E. M. (1998). Guide for all-hazard emergency operations planning. Technical report.

Bailey, M. (2024). Measuring candidate ideology from congressional tweets and websites. Available at SSRN 4350550.

Benegal, S. D. and L. A. Scruggs (2018). Correcting misinformation about climate change: the impact of partisanship in an experimental setting. *Climatic Change 148*, 61–80.

Bonica, A. (2017). Professional networks, early fundraising, and electoral success. *Election Law Journal 16*(1).

Brulle, R. J., J. Carmichael, and J. C. Jenkins (2012). Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the us, 2002–2010. *Climatic Change 114*(2), 169–188.

Canes-Wrone, B., D. W. Brady, and J. F. Cogan (2002). Out of step, out of office: Electoral accountability and house members' voting. *Annual Review of Political Science 96*, 127–140.

Canon, D. T. (1990). *Actors, Athletes, and Astronauts: Political Amateurs in the United States Congress*. Chicago University Press.

Cassella, C., E. J. Fagan, and S. M. Theriault (2023). Partisan asymmetries in earmark representation. *Political Research Quarterly 76*(4), 794–1804.

Coley, J. S. and D. J. Hess (2012). Green energy laws and republican legislators in the united states. *Energy Policy 48*, 576–583.

Cox, G. W. and M. D. McCubbins (2005). *Setting the agenda: Responsible party government in the US House of Representatives*. Cambridge University Press.

Cryer, J. (2019). Navigating identity in campaign messaging: The influence of race & gender on strategy in u.s. congressional elections. Presented at the 2019 National Conference of Black Political Scientists Annual Meeting.

Curry, J. M. and F. E. Lee (2019). Non-party government: Bipartisan lawmaking and party power in congress. *Perspectives on Politics*, 47–65.

Denny, M. J. and A. Spirling (2018). Text preprocessing for unsupervised learning: Why it matters, when it misleads, and what to do about it. *Political Analysis 26*(2), 168–189.

Dolan, K. (2005). Do women candidates play to gender stereotypes? do men candidates play to women? candidate sex and issues priorities on campaign websites. *Political Research Quarterly 58*(1), 31–44.

Druckman, J. N., M. J. Kifer, and M. Parkin (2009a). Campaign communications in us congressional elections. *American Political Science Review 103*(3), 343–366.

Druckman, J. N., M. J. Kifer, and M. Parkin (2009b). Campaign communications in u.s. congressional elections. *American Political Science Review 103*(3), 343–366.

Egan, P. J. and M. Mullin (2023). Us partisan polarization on climate change: Can stalemate give way to opportunity? *PS: Political Science and Politics 1-6*.

Feldman, L. and P. S. Hart (2018). Climate change as a polarizing cue: Framing effects on public support for low-carbon energy policies. *Global Environmental Change 51*, 54–66.

Fenno, R. F. (1978). *Home Style: House Members in Their Districts*. Boston: Little, Brown, and Company.

Gagliarducci, S. and M. D. Paserman (2022). Gender differences in cooperative environments? evidence from the us congress. *The Economics Journal 132*(641), 218–257.

Gagliarducci, S., M. D. Paserman, and E. Patacchini. (2019). Hurricanes, climate change policies and electoral accountability. *National Bureau of Economic Research*.

Garg, N., L. Schiebinger, D. Jurafsky, and J. Zou (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences 115*(16), E3635–E3644.

Goplerud, M. (2016). Crossing the boundaries: An implementation of two methods for projecting data across boundary changes. *Political Analysis*, 121–129.

Green, B., W. Hobbs, P. Rodriguez, A. Spirling, and B. M. Stewart (2024). Measuring distances in high dimensional spaces: Why average group vector comparisons exhibit bias, and what to do about it.

Grose, C. R. and B. I. Oppenheimer (2007). The iraq war, partisanship,and candidate attributes:variation in partisan swingin the 2006 u.s. house elections. *Legislative Studies Quarterly 32*(4), 531–557.

Guber, D. L., J. Bohr, and R. E. Dunlap (2021). Time to wake up: Climate change advocacy in a polarized congress, 1996-2015. *Environmental Politics 30*(4), 538–558.

Hai, Z. and R. L. Perlman (2022). Extreme weather events and the politics of climate change attribution. *Science 8*(36).

Harris, D. B. (2005). Orchestrating party talk: A party-based view of one-minute speeches in the house of representatives. *Legislative Studies Quarterly 30*(1), 127–141.

Herring, D. (2020). What is an ”extreme event”? is there evidence that global warming has caused or contributed to any particular extreme event? Technical report, National Oceanic and Atmospheric Administration.

Herrnson, P. S., C. Panagopoulos, and K. Bailey (2019). *Congressional Elections: Campaigning at Home and in Washington* (8th ed.). CQ Press.

Herrnstadt, E. and E. Muehlegger (2014). Weather, salience of climate change and congressional voting. *Journal of Environmental Economics and Management 68*(3), 435–448.

Howe, P. D., M. Mildenberger, J. R. Marlon, and A. Leiserowitz (2015). Geographic variation in opinions on climate change at state and local scales in the usa. *Nature Climate Change 5*,

596–603.
Hsiang, S., R. Kopp, A. J. adn James Rising, M. Delgado, S. W. Rosenberg, D. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larson, and T. Houser (2017). Estimating economic damage from climate change in the united states. *Science 356*(6345), 1362–1369.
IPCC (2023). Climate change 2023 sythesis report. Technical report.
Jacobson, G. C. (1989). Strategic politicians and the dynamics of u.s. house elections, 1946-86. *American Political Science Review 83*(3), 773–793.
Khodak, M., N. Saunshi, Y. Liang, T. Ma, B. Stewart, and S. Arora (2018). A la carte embedding: Cheap but effective induction of semantic feature vectors. *Proceedings of the Association of Computational Linguistics*.
Kitagawa, R. and F. Shen-Bayh (2024). Measuring political narratives in african news media:a word embeddings approach. *Journal of Politics*.
Kozlowski, A. C., M. Taddy, and J. A. Evans (2019). The geometry of culture: Analyzing meaning through word embeddings. *American Sociological Review 84*(5), 905–949.
Lahsen, M., G. de Azevedo Couto, and I. Lorenzoni (2020). When climate change is not blamed: the politics of disaster attribution in international perspective. *Climatic Change 158*(213–233).
Lazarus, J. (2008). Why do experienced challengers do better than amateurs? *Political Behavior 30*(2), 185–198.
Leuthold, D. A. (1968). *Electioneering in a democracy: Campaigns for Congress*. John Wiley and Sons.
Liao, Y. and P. R. Junco (2022). Extreme weather and the politics of climate change: A study of campaign finance and elections. *Journal of Environmental Economics and Management 111*.
Maestas, C. D. and C. R. Rugeley (2008). Assessing the "experience bonus" through examining strategic entry, candidate quality, and campaign receipts in u.s. house elections. *American Journal of Political Science 52*(3), 520–535.
Maisel, L. S. and W. J. Stone (1997, February). Determinants of candidate emergence in u.s. house elections: An exploratory study. *Legislative Studies Quarterly 22*, 79–96.
Maisel, S. L. (1986). *From Obscurity to Oblivion: Running in the Congressional Primary*. University of Tennessee Press.
Manley, D. K., V. A. Hines, M. W. Jordan, and R. E. Stoltz (2013). A survey of energy policy priorities in the united states: Energy supply security, economics, and the environment. *Energy Policy 60*, 687–696.
Mansbridge, J. (2003). Rethinking representation. *American Political Science Review 97*(4), 515–528.
Marlon, J. R., X. Wang, P. Bergquist, P. D. Howe, A. Leiserowitz, E. Maibach, M. Mildenberger, and S. Rosenthal (2022). Change in us state-level public opinion about climate change: 2008–2020. *Environmental Research Letters 17*.
Mayhew, D. R. (1974). *Congress: The Electoral Connection*. New Haven: Yale University Press.
McDonald, M., R. Porter, and S. Treul (2020). Running as a woman?: Candidate presentation in the 2018 midterms. *Political Research Quarterly*.
Mildenberger, M., J. R. Marlon, P. D. Howe, and A. Leiserowitz (2017). The spatial distribution of republican and democratic climate opinions at state and local scales. *Climatic Change 145*, 539–548.
Pearse, R. (2017). Gender and climate change. *Wiley Interdisciplinary Reviews: Climate Change 8*(2).

Pearson, K. (2015). *Party discipline in the US House of Representatives*. University of Michigan Press.

Porter, R. (2022). *Some Politics Are Still Local: Strategic Position Taking in Congress & Elections*. Ph. D. thesis, University of North Carolina at Chapel Hill.

Porter, R. and T. Steelman (2023). No experience required: Early donations and amateur candidate success in primary elections. *Legislative Studies Quarterly 48*(2), 455–466.

Porter, R. and S. A. Treul (2024). Evaluating (in)experience in congressional elections. *American Journal of Political Science*.

Porter, R., S. A. Treul, and C. R. Case (2024). Congressional campaign website project.

Porter, R., S. A. Treul, and M. McDonald (2024). Changing the dialouge: Descriptive candidacies & position-taking in campaigns for the u.s. house of representatives. *Journal of Politics*.

Prener, C. (2020). Areal weighted interpolation. https://slu-opengis.github.io/areal/articles/areal-weighted-interpolation.html.

Raimi, D., S. Carley, and D. Konisky (2022). Mapping county-level vulnerability to the energy transition in us fossil fuel communities. *Scientific Reports 12*(1).

Reed, K. A., M. F. Wehner, and C. M. Zarzycki (2022). Attribution of 2020 hurricane season extreme rainfall to human-induced climate change. *Nature Communications 13*.

Rodriguez, P. L. and A. Spirling (2022). Word embeddings: What works, what doesn't, and how to tell the difference for applied research. *The Journal of Politics 84*(1), 101–115.

Rodriguez, P. L., A. Spirling, and B. M. Stewart. (2023). Embedding regression: Models for context-specific description and inference. *American Political Science Review 117*(4), 1255–1274.

Rohde, D. W. (1979, February). Risk bearing and progressive ambition: The case of members of the united states house of representatives. *American Journal of Political Science 23*(1), 1–26.

Russell, A. (2021). *Tweeting is leading: how senators communicate and represent in the age of Twitter*. Oxford University Press.

Snyder Jr., J. M. and T. Groseclose (2000). Estimating party influence in congressional roll-call voting. *American Journal of Political Science 44*(2), 193–211.

Steelman, T. and J. A. Curiel (2023). The accuracy of identifying constituencies with geographic assignment within state legislative districts. *State Politics & Policy Quarterly 23*(2), 218–232.

Stokes, L. C. (2016). Electoral backlash against climate policy: A natural experiment on retrospective voting and local resistance to public policy. *American Journal of Political Science 60*(4), 958–974.

Sulkin, T. (2005). *Issue politics in Congress*. Cambridge University Press.

Sulkin, T., C. M. Moriarty, and V. Hefner (2007). Congressional candidates' issue agendas on- and off-line. *The International Journal of Press/Politics 12*(2), 63–79.

Thomsen, D. M. (2022). Competition in congressional elections: Money versus votes. *American Political Science Review*, 1–17.

Wolsink, M. (2020). Framing in renewable energy policies: A glossary. *Energies 13*(11).

Wynes, S., M. Dickau, J. E. Kotcher, J. Thaker, M. H. Goldberg, H. D. Matthews, and S. D. Donner (2022). Frequent pro-climate messaging does not predict pro-climate voting by united states legislators. *Enviornmental Research: Climate 1*(2).

Xenos, M. A. and K. A. Foot (2005). Politics as usual, or politics unusual? position taking and dialogue on campaign websites in the 2002 u.s. elections. *Journal of Communication 55*(1), Pages 169–185.

# Online Appendix for: Communicating on Climate Change

Ben Francis, Rachel Porter, and Bill Kakenmaster

## Contents

# A Data Collection: Congressional Campaign Websites

## A.1 Motivation

Campaign websites are a data source well-suited for our purposes because they provide an inventory of issues important to a candidate's campaign (i.e., they are complete) and come directly from a candidate's campaign (i.e., they are unmediated). Campaign websites are also an increasingly popular data source in political science research because of their widespread adoption, making them largely representative of the population of campaigns (e.g., Dolan 2005; Cryer 2019; McDonald et al. 2020; Bailey 2024). Candidates and their staff are deliberate when crafting their website position taking because these sites serve as a "hub" for campaign information. These sites are also visited by electoral stakeholders, like would-be constituents and potential donors (Druckman et al., 2009b; Herrnson et al., 2019), so it behooves a candidate to paint a complete picture of themselves on their websites. Social media provides an alternative source for data on campaign position taking. These mediums supply researchers with a monumental amount of data on candidate campaign behavior. However, a candidate's use of social media like Twitter and Facebook depends greatly on her political sophistication (Lassen and Brown, 2011), partisanship (Vogels, Auxier and Anderson, 2021) and intended audience (Das et al., 2022). Furthermore, with the shutdown of multiple public platforms for research on social media (e.g., the Twitter API in 2023 and the Facebook API in 2018) these data are becoming increasingly inaccessible. Finally, it is unclear to what extent a candidate's social media behavior well-reflects the broader policy focus of her campaign; such uncertainty does not exist with regard to position taking on websites. Existing work compares the stances a candidate lists on her campaign website to her positions taken in other venues (i.e., speeches, debates, and advertisements), finding remarkably consistency in position taking behavior across these sources (Xenos and Foot, 2005; Sulkin et al., 2007).

## A.2 Data Collection Strategy

The campaign website data collected for this project belongs to a broader, longitudinal study about the nature of elite communication in contemporary congressional elections by Porter et al. (2024). Our analyses rely on the complete corpus of congressional campaign platforms collected by Porter et al. (2024). At the time of our initial data collection, this paper's development was in a nascent stage; therefore, the initial collection and labeling of campaign platform text was completed agnostic to the researcher's objectives for this paper. A brief description of the data collection effort by Porter et al. (2024) is included to follow. For a complete review, see Porter et al. (Forthcoming).

To collect text data from candidate campaign websites, Porter et al. (2024) first identified the names of all major party candidates running in 2018, 2020, and 2022 using candidate filings with the Federal Election Commission (FEC), as well as state-level elections websites. Using this list of names, they sought to identify the campaign website URLs for all candidates in each election year by following links from online repositories like Politics1.com, visiting candidates' social media pages, and conducting simple Google searches. A small group of candidates running in primaries from 2018 to 2022 either had no official campaign website. Of the 6,080 congressional candidates who emerged to run between 2018 and 2020, about 85% had a campaign website. A team of research assistants were tasked with cataloging campaign website text for each election. Each RA was assigned a random selection of candidate names and website URLs. To ensure consistency, text was collected the day before or the day of each candidate's congressional primary. To collect campaign website text data, RAs would first navigate to a candidate's website and verify that the URL matched their candidate's profile (i.e., ensure the right website was assigned to the right candidate). Then, using a Qualtrics tracking survey, RAs were instructed to indicate whether or not a campaign platform could be identified on a candidate's campaign website. We define a campaign platform as a collection of stated stances on policy or policy goals. A platform page or pages could almost always be found on the website's "main menu." RAs were instructed to copy/paste the entirety of text contents from campaign platforms into the Qualtrics tracking survey. Some candidates who adopted a campaign website did not outline any policy positions on that site. About 15% of all congressional candidates that had a campaign website did not adopt a campaign platform on that site.

# B Units of Analysis

Our analyses are interested in capturing the strategic position taking behavior of congressional candidates running for the U.S. House of Representatives. However, not all candidates running for Congress behave strategically. A bevy of studies find that a sizable proportion of congressional candidates emerge each election cycle in pursuit of non-political and non-electoral goals; for instance, seeking to gain material benefits or advance their professional careers (Leuthold, 1968; Maisel, 1986; Canon, 1990; Maisel and Stone, 1997). Candidate motivations have important downstream consequences on strategic campaign behavior. In particular, Porter et al. (2024) find that "professional" candidates who are mounting a credible run for office tailor their position taking behavior to their electoral and district context. Truly "amateur" candidates, on the other hand, are often agnostic towards their electoral environment and do not tailor their position taking behavior; these individuals are running for their own purposes—not necessarily to win. Because we are interested in examining if and how a candidate's local district context impacts their climate change position taking, we constrain our analyses to include only "professional" or serious candidates. Traditionally, previous elected experience has been used as the standard ex ante predictor for campaign viability or "quality" in congressional elections research (Jacobson, 1989; Lazarus, 2008). More recent work, however, has found prior officeholding experience is no longer a consistent predictor for candidate quality and campaign professionalism (Maestas and Rugeley, 2008; Bonica, 2017; Porter and Steelman, 2023; Porter and Treul, 2024; Algara and Bae, 2024). Following this research, we rely on campaign fundraising as a barometer for candidate viability.

To select our fundraising threshold, we examined the fundraising potential of all candidates who filed with the Federal Election Commission (FEC).[16] In our time series, the average U.S. House incumbent raised $2,600,002 and the median incumbent raised $1,705,609 in a single campaign cycle (primary and general election). The average non-incumbent candidate raised $695,785 and the median non-incumbent raised $141,664 (primary and general election). The average non-incumbent candidate who lost their primary raised $275,732 and the median candidate raised $86,911. Based on this, we selected the threshold of $75,000. Variations in this cut-off threshold (+/- $25,000) do not impact the substantive takeaways of our main paper analysis.[17]

[16] In calculating the fundraising distribution of congressional candidates, we excluded candidates who reported less than $5,000 of fundraising and, therefore, did not file paperwork with the FEC.

[17] Using this threshold, 100% of incumbent members of the U.S. House who ran between 2018 and 2022 are considered serious candidates. Of non-incumbents, 76% of prior officeholders and 37% of candidates without prior elected experience are considered serious candidates.

Of those 6,006 major party candidates who ran for the U.S. House of Representatives between 2018 and 2022, a total of 2,628 (44%) met our selection criteria for inclusion in our analyses (i.e., had a campaign website with a policy platform and qualified as a "serious" candidate). A total of 2,773 candidates were excluded from our analyses for not qualifying as "serious." From those remaining candidates, another 605 candidates were excluded because did not have a campaign website with a policy platform.

### B.1 Descriptives on Campaign Platform Adoption

### B.2 Descriptives on Climate Policy Discussion

## C Key Independent Variables

### C.1 Threat of Inaction: Risk of Natural Hazard

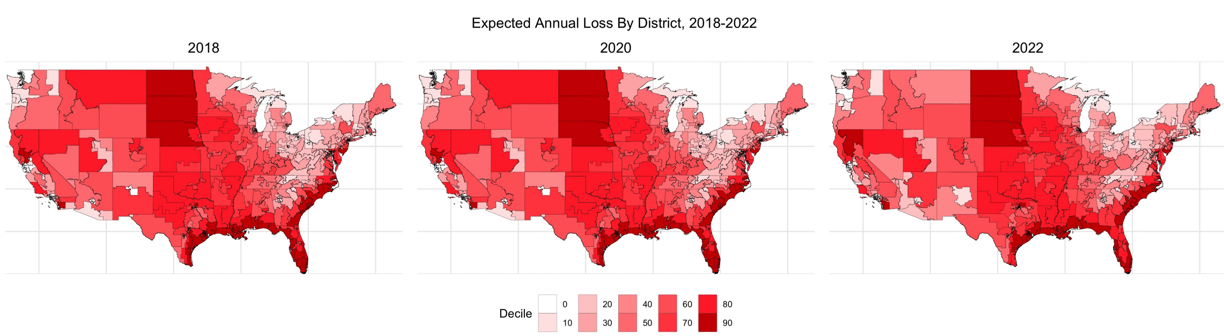
The FEMA National Risk Index (NRI) was designed to illustrate the susceptibility of U.S. communities to natural hazards. The basis of the Index is a measurement of expected annual loss (EAL), which quantifies the average economic loss in dollars resulting from 18 different natural hazards (e.g., flood, heat waves, hurricanes, and earthquakes) each year. EAL is calculated by multiplying a community's exposure (i.e., the value of buildings, population, and agriculture that might be exposed to natural hazards) by the community's annualized frequency of natural hazard occurrence and historic rates of loss due to past natural hazards. Each community's EAL is then weighted by measures of vulnerability and resilience to produce FEMA's Natural Risk Index. A community's vulnerability is defined as the susceptibility of its social groups to the adverse impacts of natural hazards, and is operationalized using a 16 socioeconomic variables (e.g., poverty rate, unemployment, housing type, and health insurance coverage). A community's resilience capability is defined as its perceived ability to prepare for, adapt to, withstand, and recover from the effects of natural hazards. Data on community resilience is provided by the University of South Carolina's Hazards Vulnerability & Resilience Institute. Communities with higher social vulnerability are computed as at greater natural hazard risk; communities with higher resiliency are computed as at less natural hazard risk. Greater detail regarding the FEMA's data and methodological approach for creating this Risk Index can be found at: https://www.fema.gov/sites/default/files/documents/fema_national-risk-index_technical-documentation.pdf.

In our main paper analyses, we elect to rely on census tract-level estimates of EAL rather than the full National Risk Index described above to assess elite rhetoric on climate attribution. Our theoretical argument ties Republican candidates' propensity to engage in climate change attribution to their perceptions of the immediate risk that their district faces, rather than their perceptions of their district's ability to withstand climate risk. FEMA's estimated EAL better captures this relationship than their NRI. Moreover, there is also concern that community resilience and vulnerability may correlate with demographic and socioeconomic characteristics that predict a community's partisanship; in this case, using FEMA's NRI could conflate these two constructs. Finally, FEMA's measures for EAL and NRI do not explicitly account for climate change and include two natural hazards (i.e., volcanic activity and earthquakes) that are orthogonal to climate change. Based on available data, we are able to calculate an adjusted measure of EAL for communities that excludes natural hazard costs incurred from earthquakes and volcanic activity; we are not able to produce this kind of adjusted measure of FEMA's NRI.

To transform FEMA's census tract estimates of EAL to our target unit of aggregation (i.e., congressional districts), we use a method for areal weighted interpolation. This technique uses known quantities to estimate values for overlapping, but incongruent, polygon features. We specifically employ extensive areal interpolation, where census tract data are weighted based on their areal intersection with congressional districts.[18] Areal interpolation relies on an assumption that populations are spread evenly across census tracts. If density is consistent, then the boundaries of counties are inconsequential to estimations. If density *is not* consistent, then changing county boundaries could yield different district estimates. This dilemma is called the modifiable areal unit problem (MAUP).[19] Violating this assumption induces unpredictable statistical bias into our district-level estimates, which could impact results. Work by Steelman and Curiel (2023) addresses some of this concern about measurement bias, demonstrating that areal interpolation performs reasonably well at recovering accurate estimates for large units of aggregation. We provide an additional robustness check on our methodological approach in Section C.3 and find a strong correlation between our interpolated district-level estimates and estimates produced by other researchers using multilevel regression with postratification (MRP).

Although longitudinal data for FEMA's NRI and EAL estimates are available, archived data versions reflect both updates to source data *and* methods. Therefore, we cannot be sure that changes in older data versions reflect actual risk change rather than shifts in methodological choices. For this reason, we employ the March 2023 release of the FEMA's National Risk data—which relies on data collected between June 2021 and December 2022—to calculate our estimates of congressional district risk for all election years in our analysis. To try and best capture a district's natural hazard risk for each unique election cycle in our data, we areal interpolate these 2023 EAL estimates using the 116th U.S. Congressional District boundaries for the 2018 election, the 117th U.S. Congressional District boundaries for the 2020 election, and 118th U.S. Congressional District boundaries for the 2022 election. District-level estimates for expected annual loss by year are displayed in Figure C.1; this continuous variable has been discretized into the deciles employed in our main paper analysis.

Figure C.1: Map of Expected Annual Loss for Climate-Related Natural Hazards




[18]For more details on weighting implementation, see Prener (2020).

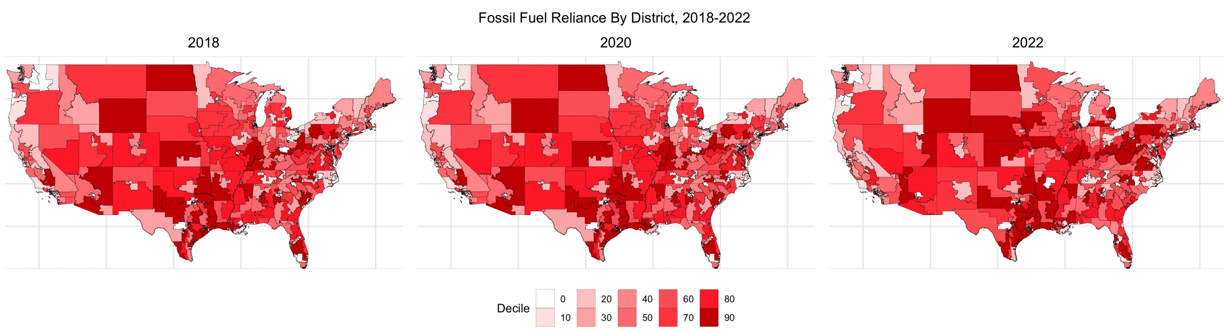
[19]For a more complete description of MAUP, see Goplerud (2016).

## C.2 Threat of Action: Reliance of Fossil Fuels

The U.S. Energy Information Administration (EIA) provides fine-grain data on operable power plants with an energy production capacity of 1 megawatt or more within the United States. Information provided about each power plant includes its relative reliance on fossil (e.g., oil, goal, and natural gas) and non-fossil (e.g., wind, solar, and hydroelectric) energy sources, production capacity, and geolocation. We rely on these data to estimate each congressional district's reliance on fossil fuels. Greater detail regarding power plant data made publicly available by the U.S. EIA can be found at: https://eia.maps.arcgis.com/home/item.html?id=bf5c5110b1b944d299bb683cdbd02d2a.

For each operable power plant, we calculate the energy production from fossil sources. Next, we use the latitudinal and longitudinal coordinates provided in the EIA data to geolocate power plants within congressional districts. We geolocate power plants using the 116th U.S. Congressional District boundaries for the 2018 election, the 117th U.S. Congressional District boundaries for the 2020 election, and 118th U.S. Congressional District boundaries for the 2022 election. Once each power plant has been geolocated, we calculate a sum total fossil energy production at the congressional district-level. District-level estimates for expected annual loss by year are displayed in Figure C.2; this continuous variable has been discretized into the deciles employed in our main paper analysis.

Figure C.2: Map of Total Megawatts Produced with Fossil Fuel Energy Sources




The data release used to generate our estimate of congressional district energy production are from EIA data collected through May 2023. Some of the power plants present in these data were not yet operational for the earlier election years in our data. To produce more accurate estimates of energy production capacity for each election cycle, we merged in information that identified the year each power plant was commissioned. When calculating energy production capacity for each congressional district, we included only those power plants that were commissioned on or before that election year. We could not identify the commission year for 161 of the 11,946 power plants present in our data. Therefore, we include these power plants in energy production capacity estimates for all congressional districts across all election years. These plants compose only 1% of all facilities present in our data and only a fraction of a percent (0.009%) of total U.S. energy production. Nearly all the power plants missing a commission date in our data relied principally on solar and wind energy sources.

## C.3 Public Opinion on Climate Change

The Yale Program on Climate Change Communication fields an annual survey assessing public opinion on climate change across multiple dimensions. This large survey is fielded every fall and is nationally representative. We employ the following survey question in our main paper analysis to capture respondents' perceptions regarding climate risk:

How strongly do you agree or disagree with this statement?: Global warming is affecting the weather in the United States

- Strongly agree
- Somewhat agree
- Somewhat disagree
- Strongly disagree

Public opinion estimates for this question are reported as the percentage of respondents for a given geographic unit who answered they "Strongly agree" or "Somewhat agree" with this statement about climate change and weather. We employ a different survey question to capture respondents' perceptions regarding renewable energy:

How much do you support or oppose funding more research into renewable energy sources, such as solar and wind power?

- Strongly support
- Somewhat support
- Somewhat oppose
- Strongly oppose

Public opinion estimates for this question are reported as the percentage of respondents for a given geographic unit who answered they "Strongly support" or "Somewhat support" this renewable energy policy. Because the Yale Climate Opinion survey is nationally representative, public opinion estimates for sub-national geographic units are derived from a statistical model using multilevel regression with post-stratification (MRP). These MRP estimates for 2010-2020 are provided by Marlon et al. (2022) and estimates for 2021-2023 are provided by Howe et al. (2015). The lowest unit of aggregation available longitudinally for these estimates is the county-level. To aggregate counties into congressional districts, we employ the same areal interpolation approach described above, but rely on spatially intensive interpolation rather than spatially extensive interpolation because data are percentage values rather than summed dollar amounts. Several counties lack public opinion estimates; a total of five congressional districts across 2018, 2020, and 2020 encompassed at least one county with null values. We drop these counties when producing our areal weighted interpolation estimates of district-level public opinion.

To provide a robustness check on our methodological approach, we correlate our interpolated estimates for district-level public opinion in 2022 with MRP estimates of district-level opinion made available by Marlon et al. (2022) for 118th Congressional District boundaries. For the survey questions about global warming and weather, we find a correlation of 0.92 between our interpolated estimates of public support and MRP estimates provided by Marlon et al. (2022). For the survey questions about funding renewable energy research, we find a correlation of 0.86 between our interpolated estimates of public support and MRP estimates provided by Marlon et al. (2022).

## C.4 Control Variables

To capture the underlying partisan composure of each district, we rely a district's average two-party presidential vote share. Averages were computed separately for those elections between redistricting cycles will boundaries shifted (most often due to court-mandated changes to district lines). Districts are considered safe for a candidate's party if their party's presidential vote share in the district was greater than 60%. Districts are considered competitive for both party's if presidential vote share in the district was less than 60% and greater than 40%. All other districts are considered safe for the other party. We also control for whether or not a district was open (i.e., no incumbent running) in our embedding regression. We include several control variables for candidate-specific characteristics that may affect a candidate's strategic position taking on climate and energy policy. In particular, we control for a candidate's gender (male vs. non-male) and a candidate's past elected experience (incumbent vs. not). Existing research shows that women tend to be stronger advocates for climate policy (e.g., Pearse 2017; Gagliarducci and Paserman 2022). Moreover, because of their backgrounds as a federally-elected representative, incumbents may systematically differ in their position taking on climate change. Incumbents may face greater constraints in their position taking because of their roll call record or party's stance on issues. Data on these candidate characteristics are provided by Porter and Treul (Forthcoming).

# D Text Analysis

## D.1 Pre-Processing

In text pre-processing, we follow the best practices proposed by Denny and Spirling (2018) as well as those preset in the R package `context` from Rodriguez et al. (2023). In tokenizing our corpus, we remove punctuation, symbols, numbers, and separators (i.e., dashes). We do not stem words in our corpus. We remove all stop words (i.e., words that convey no semantic meaning such as "at", "the", and "to") as well as words with less than three letters. All tokens are set to lowercase and we trim any word that does not appear at least five times from our document feature matrix.

## D.2 Keyword Selection

When selecting those keywords we used in our analysis (shown in Table 1 of the main paper), we sought to capture different facets related to climate change attribution and investment in renewable energy. Recall that word embeddings are low-dimensional vector representations of words, and the distance between these vectors can be used to measure semantic similarity or "meaning." Thus, similar words should have similar word embedding representations. For this reason, we avoided using synonyms in our keyword selection and, instead, focused on terms that might capture different attributes of our quantities of interest.

To select our extreme weather keywords, we began by surveying existing scholarly and public-facing literature that addresses the link extreme weather events to climate change. Per the National Oceanic and Atmospheric Administration (2020), the words "extreme" and "weather" are most often used to encapsulate multiple types of natural hazards associated with climate change (i.e., hurricanes or tropical storms, flooding, heat waves, and wildfires). These terms have also been employed in other research seeking to measure climate change attribution (e.g., Hai and Perlman 2022; Lahsen et al. 2020). To include more specific references to physical impacts of climate change, we additionally included the terms "disasters" and "temperatures." Rising surface temperatures are the direct physical consequence of climate change (e.g., Environmental Protection Agency 2022), and these temperature changes are fueling extreme weather events (e.g., Reed et al. 2022). Per FEMA (1998), when the consequences of these events are severe enough, they are referred to as "disasters" because of their severity and magnitude; this stands in contrast to "emergencies" that also warrant action but have less severe consequences. We elected not to include specific types of natural hazards (e.g., hurricane, floods, droughts) in our keywords because, as FEMA's NRI demonstrates, the severity of these events' impacts are regional, which should result in regional trends of usage. Through the selection of our final keyword "catastrophic," we chose an adjective that was used most of by FEMA to describe the scope of extreme weather events.

To select our investment keywords, we adopted a similar approach. The term "investment" well encapsulates the quantity of interest we aim to capture, which is policy support, and has been similarly used in other research (e.g., Feldman and Hart 2018; Wolsink 2020). We next sought to choose a verb that indicated support, and identified the word "encourage" because it was often used in our corpus to convey support for renewable energy itself and industries surrounding renewable energy (e.g., encourage clean energy & encourage job creation). We additionally included the verb "prioritize" as a keyword because it explicitly places renewable energy ahead of fossil-based energy sources. In survey research on energy policy, the term "prioritize" is often used when asking participants to consider relative reliance on fossil and non-fossil energy sources (e.g., Manley et al. 2013). To reference policy apparatuses that reduce barriers to renewable energy adoption and investment, we included the term "incentives." We specifically chose not to use the words "subsidy" or "subsidize" because these terms can have a negative connotation within the general public. The choice of our last term "future" came directly from reading sample texts from our corpus. Many candidates used aspiration terms like "future" and "leader" to describe their outlook on the promise of renewable energy.

The terms we employ in our analyses are by no means exhaustive, and we undoubtedly could have employed a variety of alternative terms. In reading literature and reviewing our corpus, we kept a running list of terms that captured some aspect of climate change attribution and renewable energy investment. These word lists are as follows:

**climate change attribution:**
`droughts, flooding, hurricane, wildfires, dangers, consequences, risks, repercussions, heat, crises, impacts, caused, coasts, precipitation, fires, tornadoes, hail, events, cold, superstorm, rainfall, blizzard, hotter, extreme, disasters, temperatures, weather, catastrophic, catastrophes`

**renewable energy investment:**
`encourage, prioritize, incentives, future, investment, subsidize, incentivize, utilize, attract, fostering, develop, stimulate, support, forefront, adoption, leader, accelerating, spurring, transitioning, boosting, priorities, initiatives, generating`

To demonstrate that our results are robust to alternative keyword selections, we re-calculated the cosine similarity between our ALC embeddings and five randomly-chosen words from each of these lists. This process was repeated seven times. Results for these alternative specifications can be found in Appendix Figures E.6 and E.7. As these figures demonstrate, are results remain stable across a variety of random keyword selections from these word lists.

## D.3 ALC Embedding Estimation

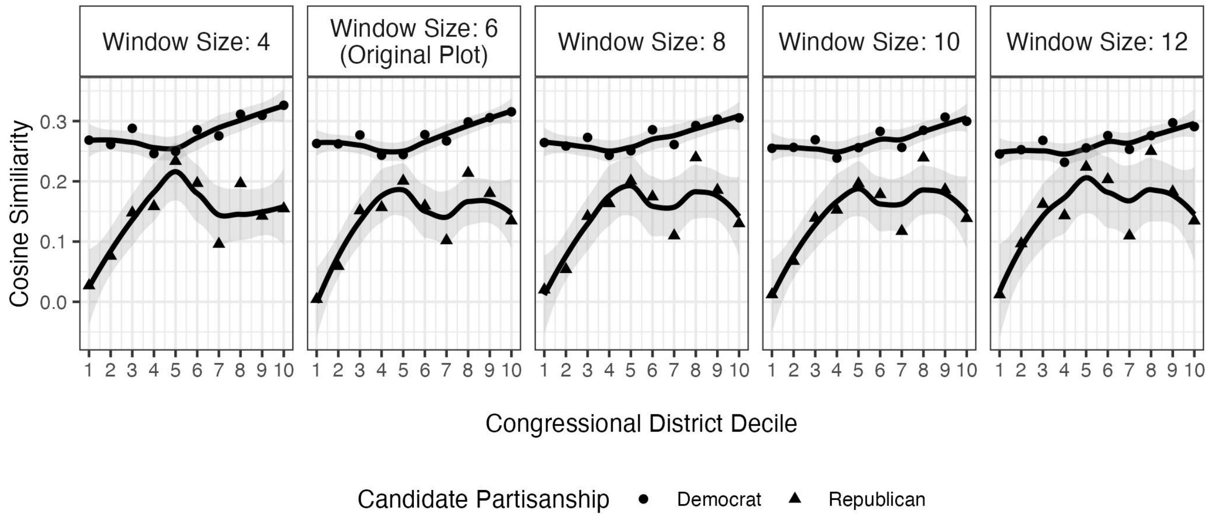
To estimate ALC embeddings across covariates of interest, we rely on the R package `context` developed by Rodriguez et al. (2023). Because our corpus is relatively small, we employ GloVe pre-trained embeddings and the corresponding transformation matrix estimated by Khodak et al. (2018). For reference, these embeddings are estimated on the English Wikipedia corpus of 4.3 million articles and 1.9 billion words. Following best practices, our ALC embeddings were generated with a 6-word context window and 300-dimensional vectors. In Figures D.1 and D.2 we demonstrate that our results are robust to different window length specifications.

We estimate four separate embedding regressions, two for our climate attribution analysis and two for our renewable energy analysis. In our climate attribution analyses, both regressions control for district-level threat, public belief that global warming affects U.S. weather, and those controls outlined in Appendix Section C.4. In each of these regressions we vary which primary independent variable is interacted with party. In our renewable energy analyses, both regressions control for district-level fossil fuel reliance, public approval of funding for renewable energy research, and those controls outlined in Appendix Section C.4. Once again, in each of these regressions we vary which primary independent variable is interacted with party. As discussed in the main paper, we discretize our primary independent variables into ten equal categories (deciles). This approach allows for non-linearity the relationship between rhetoric and key independent variables. This is important because we expect to observe the greatest shifts in Republican climate rhetoric at the minimum and maximum values of our district-level covariates. Our approach follows the approach used in extant work employing ALC word embeddings to estimate subtle changes across continuous variables. (Garg et al., 2018; Kitagawa and Shen-Bayh, 2024).

## D.4 Cosine Similarity Measurement

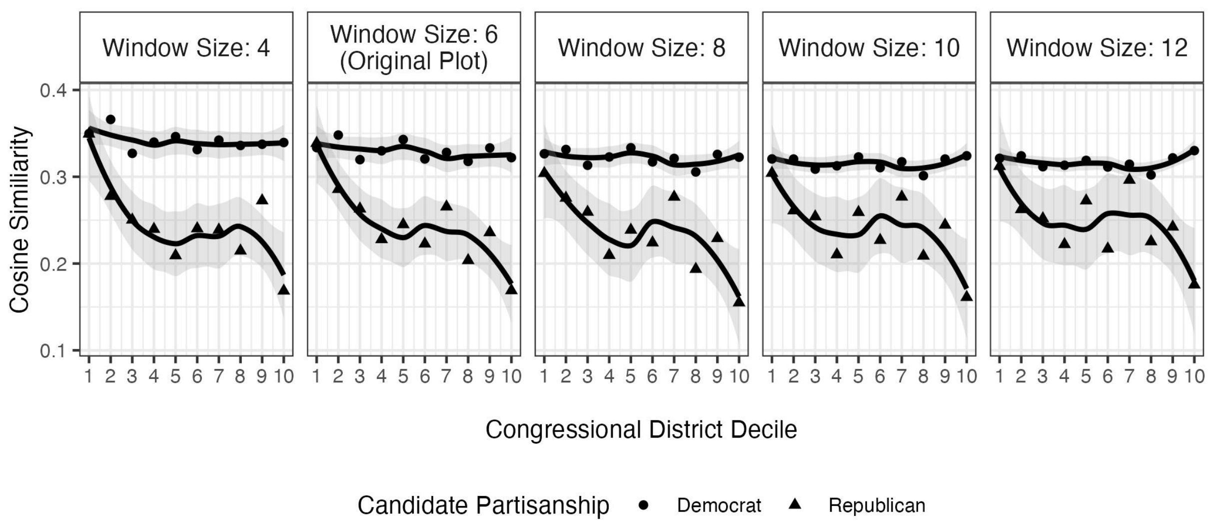
A popular metric for measuring the distance between word embedding vectors is cosine similarity, defined as $\cos(\theta) = \frac{A \cdot B}{||A||||B||}$. Cosine scores range between 1 and -1; values closer to1 (-1) indicate that words are more (less) likely to co-occur. Some recent work demonstrates that this distance measure can exhibit considerable statistical bias (Green et al., 2024). We plan to implement strategies for bias correction when they are made available by `context` package creators.

Figure D.1: Cosine Similarity Between "Climate Change" and "Global Warming" Target Phrases and Extreme Weather Keywords (Varied Context Window)




*Note:* ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as Figure 1 in the main paper, with the exception of varied context window length.

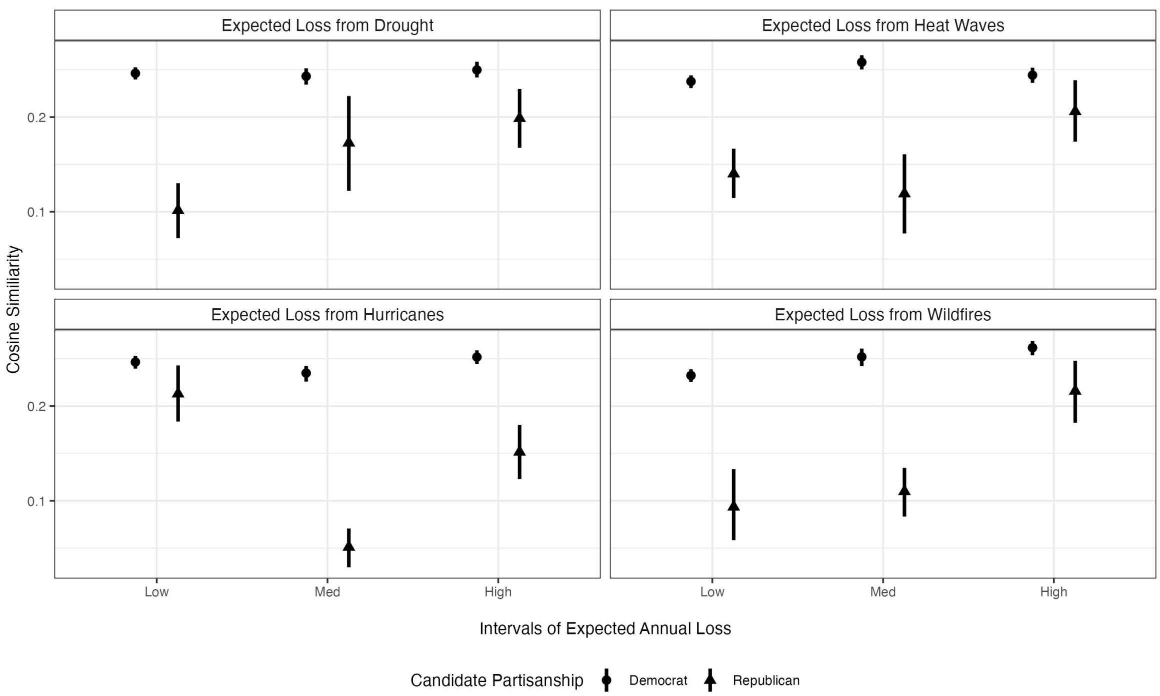
Figure D.2: Cosine Similarity Between Focal Words "Clean Energy" and "Renewable Energy" for Investment Keywords (Varied Context Window)




*Note:* ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as Figure 2 in the main paper, with the exception of varied context window length.

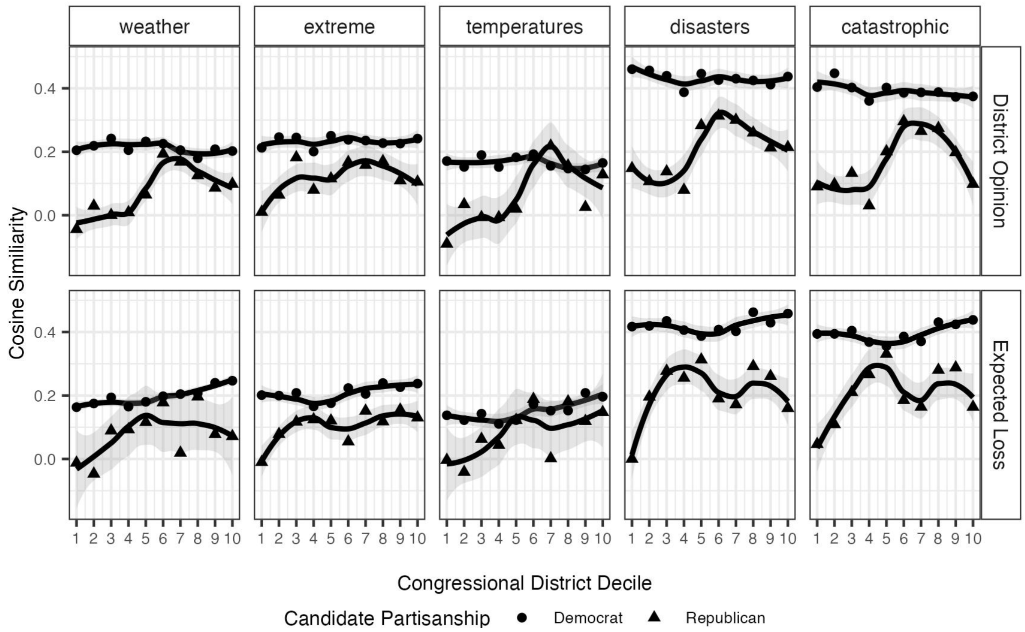
# E Supplemental Tables and Figures

Figure E.1: Cosine Similarity Between “Climate Change” and “Global Warming” Focal Phrases and Extreme Weather Keywords for Individual Disaster Events



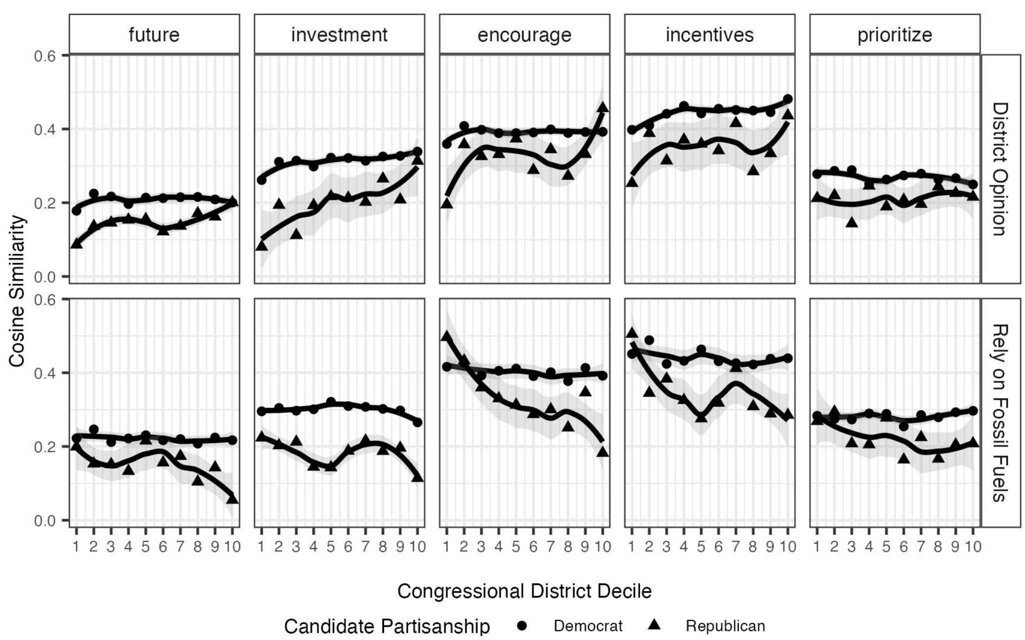

*Note:* Text pre-processing follows identical procedures employed in main paper analyses. Confidence intervals of 95% are produced through 100 bootstrapped simulations. Dollar values for expected annual loss are divided into three equal sized quantiles and are interacted with candidate party. The x-axis value of “High” indicates a value greater than or equal to the 66th percentile of EAL for that specific natural hazard across all congressional districts; “Med” indicates a value greater than or equal to the 33rd percentile and less than the 66th percentile of EAL for that specific natural hazard across districts; “Low” indicates a value less than the 33rd percentile of EAL for that specific hazard across districts.

Figure E.2: Cosine Similarity Between "Climate Change" and "Global Warming" Target Phrases for Extreme Weather Keywords (Disaggregated Results)



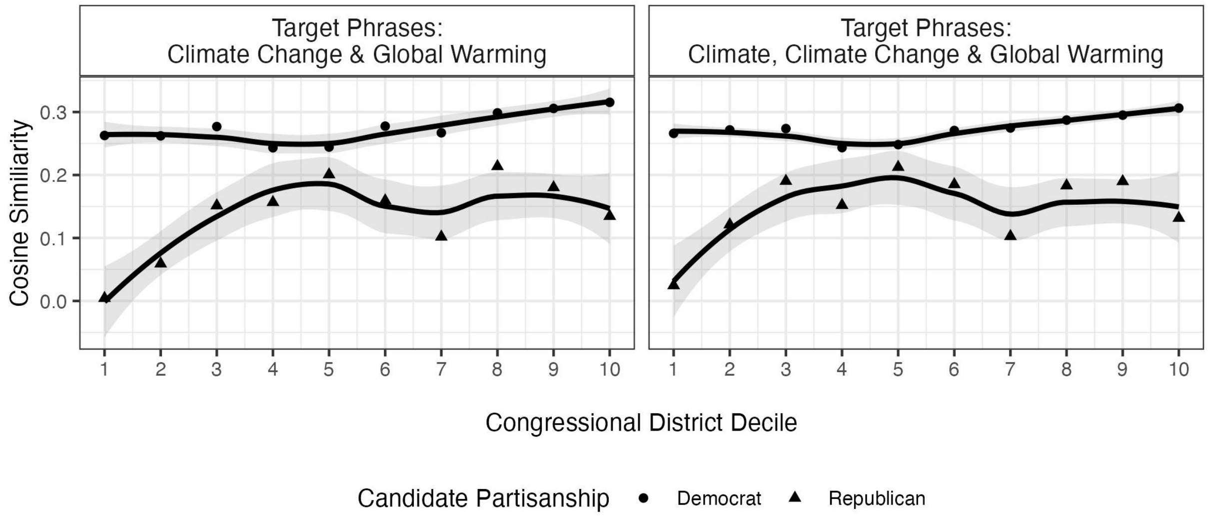

*Note:* Cosine similarities reflect individual target-keyword comparisons from Figure 1 of the main paper.

Figure E.3: Cosine Similarity Between"Renewable Energy" and "Clean Energy" Target Phrases and Investment Keywords (Disaggregated Results)



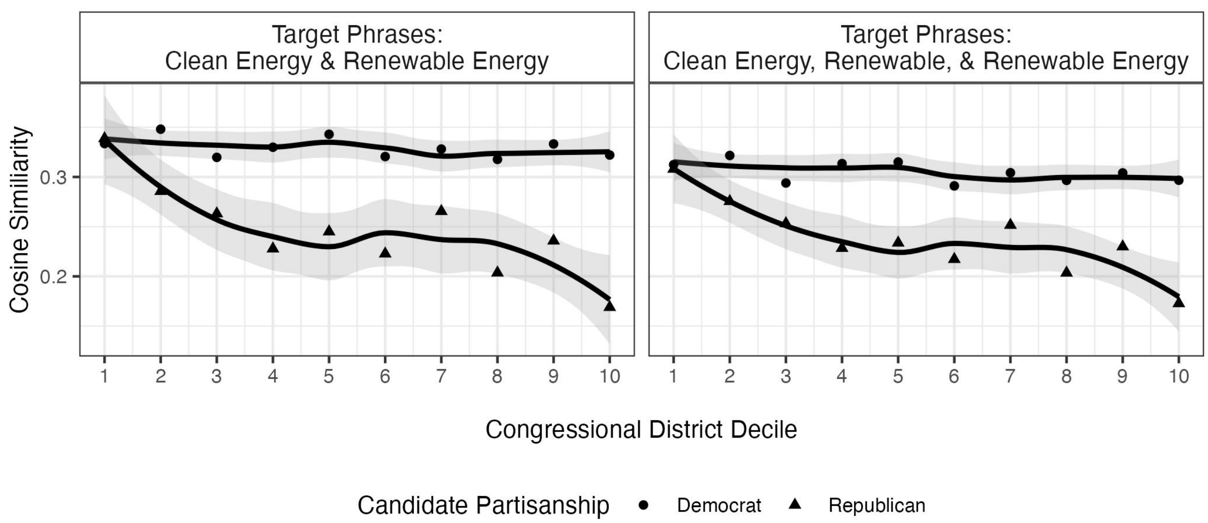

*Note:* Cosine similarities reflect individual target-keyword comparisons from Figure 2 of the main paper.

Figure E.4: Cosine Similarity Between Climate Target Phrases and Extreme Weather Keywords



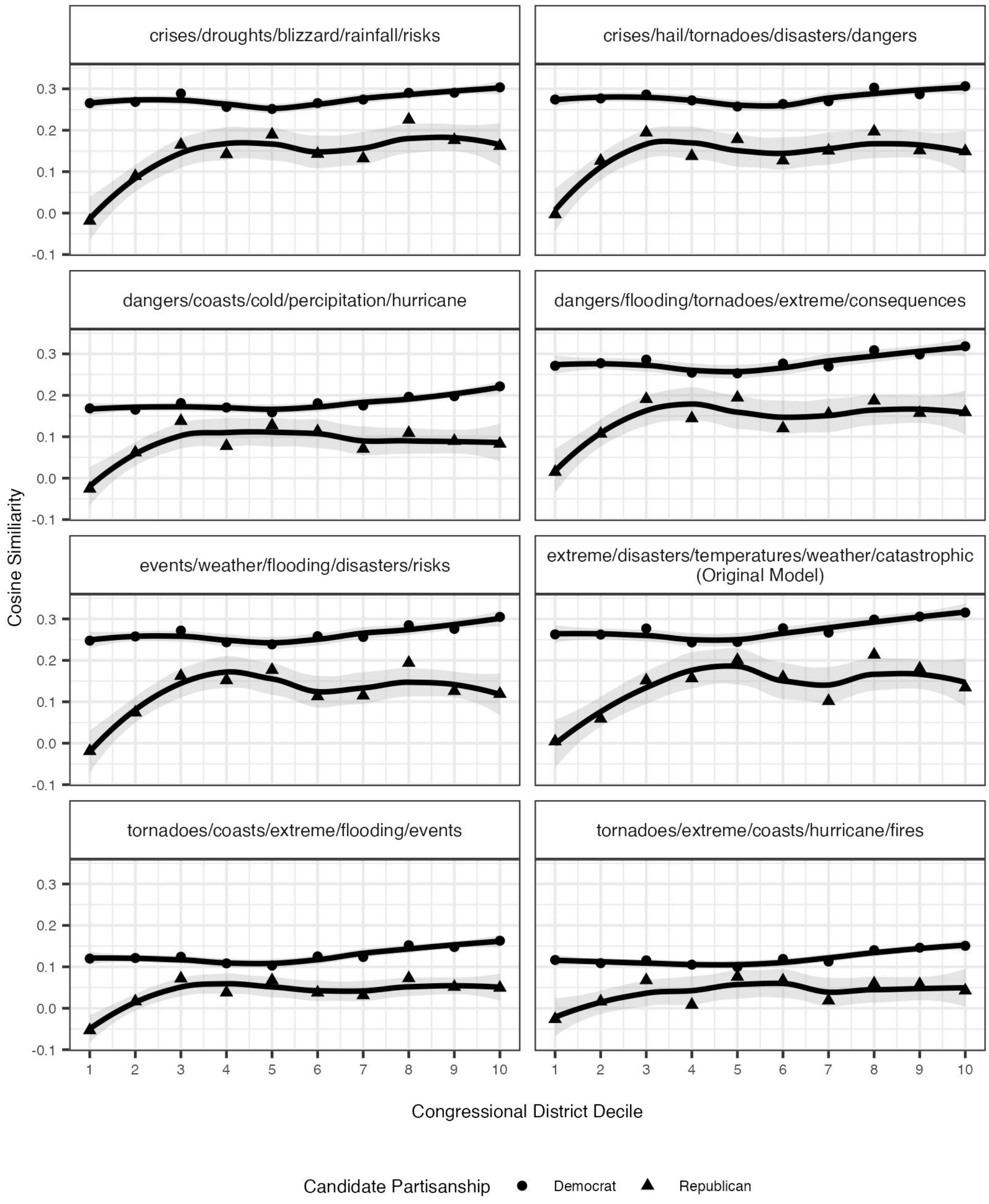

*Note:* ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as Figure 1 in the main paper. Cosine similarities reflect averages between target phrases/words and keywords.

Figure E.5: Cosine Similarity Between Energy Target Phrases and Investment Keywords



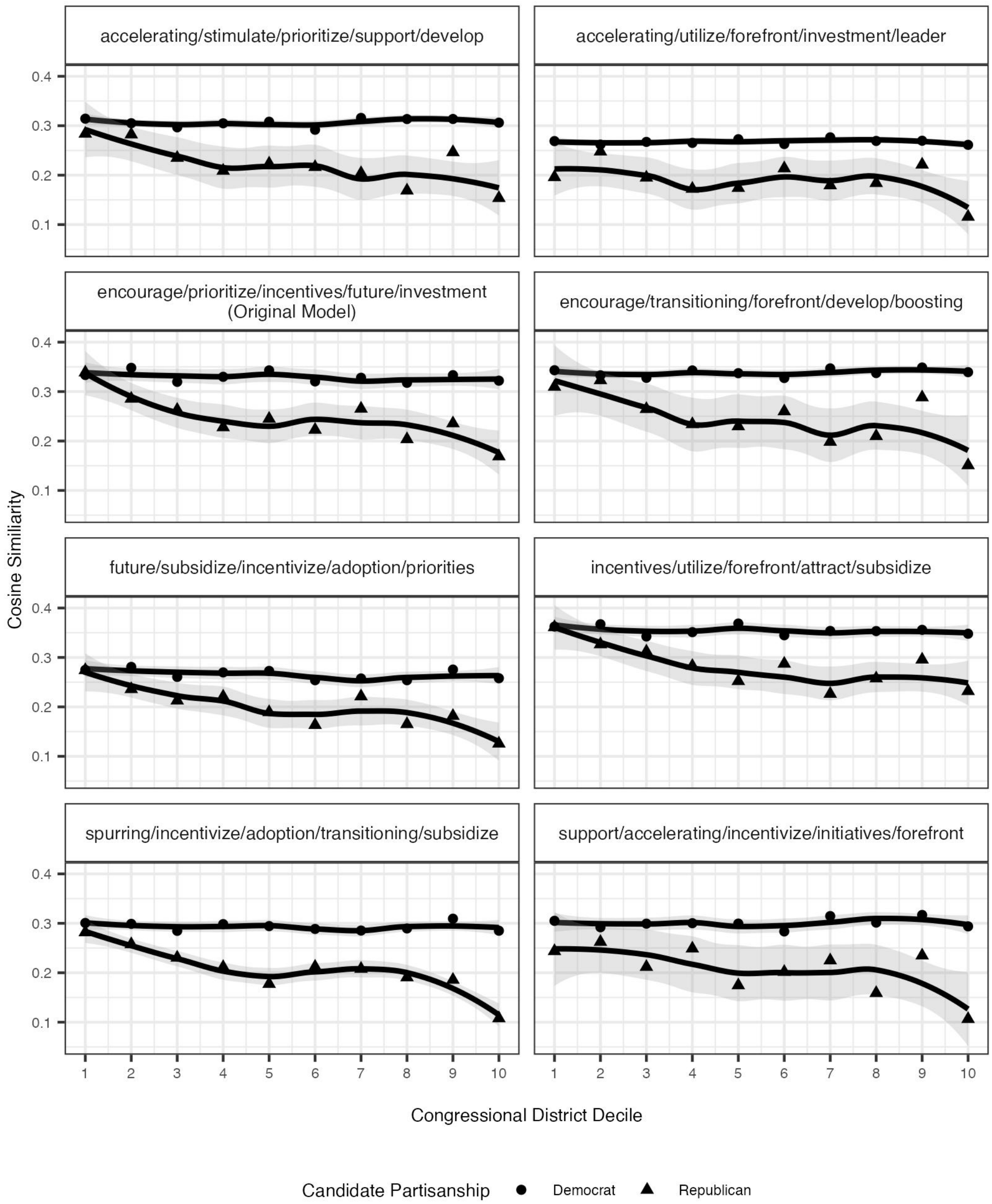

*Note:* ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as Figure 2 in the main paper. Cosine similarities reflect averages between target phrases/words and keywords.

Figure E.6: Cosine Similarity Between "Climate Change" and "Global Warming" Target Phrases and Randomly-Drawn Extreme Event Keywords




*Note:* ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as Figure 1 in the main paper. For all plots (with the exception of the original model), cosine similarity calculations are made using five extreme weather keywords are drawn randomly for the following word list: droughts, flooding, hurricane, wildfires, dangers,
consequences, risks, repercussions, heat, crises, impacts, caused, coasts, precipitation, fires, tornadoes, hail, events, cold, superstorm, rainfall, blizzard, hotter, extreme, disasters, temperatures, weather, catastrophic, catastrophes

Figure E.7: Cosine Similarity Between "Clean Energy" and "Renewable Energy" Target Phrases and Randomly-Drawn Investment Keywords




*Note:* ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as Figure 1 in the main paper. For all plots (with the exception of the original model), cosine similarity calculations are made using five extreme weather keywords are drawn randomly for the following word list: encourage, prioritize, incentives, future, investment, subsidize, incentivize, utilize, attract, fostering, develop, stimulate, support, forefront, adoption, leader, accelerating, spurring, transitioning, boosting, priorities, initiatives, generating

Table F1: Keyword Terms in Context with Anchor Phrases

| **Anchor Phrases: climate change; global warming** | |
|---|---|
| **Keyword Terms** | **Terms in Context** |
| extreme | we already see the effects of climate change in prolonged drought and extreme heat.<br>data clearly shows that climate change increases the risk and intensity of extreme weather.<br>increased risk from rising sea levels, heat waves, and extreme storms. Climate change is |
| catastrophic | to see increased extreme weather conditions that continue to spark catastrophic fires<br>the catastrophic outcomes of climate change mandate that we cut carbon pollution<br>resilient against catastrophic wildfires. For climate change advocates the amount of CO2 |
| disasters | hotter summers, and more natural disasters. We cannot continue to ignore global warming<br>climate disasters in our state and around the country such as Hurricane Ida demonstrate<br>we are already seeing its effects on our air quality, wildlife, the severity of natural disasters |
| weather | global warming would produce more severe weather events such as increased flooding<br>temperatures increase the oceans rise, glaciers shrink, and weather patterns and disasters |
| temperatures | global warming is ”unequivocal” and humans are causing most of the rise in temperatures<br>every year has seen record-breaking temperatures. Climate change presents a real threat<br>climate change is a top priority. Decades of inaction has resulted in warmer temperatures |
| **Anchor Phrases: renewable energy; clean energy** | |
| **Keyword Terms** | **Terms in Context** |
| incentives | must shift subsidies and incentives to support the renewable energy sector and companies<br>jobs training, creating incentives for clean energy innovation, encouraging companies to<br>legislation that would extend and expand clean energy incentives, like permanently |
| encourage | support policies that encourage the growth of clean, renewable energy and discontinue<br>oil and use those funds to encourage clean energy job creation in our nation’s urban cores. |
| investment | expand the use and increase investment in renewable energy. I will never support fracking<br>He’ll work to restore funding for clean energy investment, ensure the United States honors<br>Investment in clean and renewable energy will continue to create jobs, curb climate |
| prioritize | We must prioritize the protection of our environment and transition to renewable energy.<br>Let’s prioritize sectors (e.g. renewable energy) with the highest potential for job creation.<br>will prioritize a clean energy standard to ensure that by 2050, 50 percent of our power |
| future | that can be our source of prosperity as we transition to a renewable energy future.<br>threat facing humanity, and clean energy jobs are the future of Indiana’s economy<br>sweeping environmental omnibus bill, (S.2545 An Act to promote a clean energy future) |