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 candidates who ran for the U.S. House of Representatives 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 express support for renewable energy investment conditional on district-level reliance on fossil fuels for employment. Democrats display remarkable consistency in their rhetoric 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) attributing extreme weather to rising temperatures by political elites and (2) policy support for increasing renewable electricity generation (IPCC, 2023). Congressional Democrats generally support these positions more than Republicans (e.g., Guber et al. 2021; Egan and Mullin 2023). As a result, legislative responses to climate change remain largely gridlocked along party lines.

Politicians have electoral and legislative incentives to toe the party line on policy issues (e.g., Ansolabehere and Iyengar 1994). 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 (Canes-Wrone et al., 2002; Porter, 2022). This suggests that both partisanship *and* local conditions shape politicians' position-taking behavior. In this vein, some scholars suggest that Republicans may be motivated to adopt more pro-climate policy positions in response to climate-relevant conditions in their constituencies (Egan and Mullin, 2023). This idea aligns with previous research documenting variation in the climate change attitudes of Republican voters (e.g., Mildenberger et al. 2017; Marlon et al. 2022). To our knowledge, however, scant research empirically evaluates whether Republican politicians ever deviate from their party's stance on climate issues. Our paper contributes to the literature on climate change in American politics by assessing the relationship between climate-relevant factors in congressional districts and politicians' stated positions on climate attribution and renewable energy.

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 (Hoffmann et al. 2022, cf. Hazlett and Mildenberger 2020). Alternatively, they 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, we expect Republican politicians from districts with high (low) risk of climate-related disasters to more (less) closely associate extreme weather to climate change.

We also expect an association between Republican politicians' support for renewable energy and their district's reliance on fossil fuels. 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 particular, it reduces employment opportunities that rely on carbon-intensive activities (Graham and Knittel, 2024). In these districts, politicians' support for renewable energy investment can lead to a considerable electoral backlash (Stokes, 2016). On the other hand, Republicans from communities with limited reliance on fossil fuels for employment may see renewable energy investment as an opportunity to bolster and subsequently claim credit for local economic gains (Mayhew, 1974). As such, we expect Republican politicians from districts with low (high) reliance on fossil energy production and consumption for employment to more (less) closely associate renewable energy with policy investments.

To evaluate politicians' rhetoric on climate change, we analyze a corpus of campaign platforms from candidates who ran for the U.S. House of Representatives 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 how contextual word usage shifts with district-level factors. We find that, among candidates running in districts with high expected costs from climate-related disasters, both Democrats and Republicans closely associate climate change with extreme weather events. However, as the expected cost of climate-related disasters decreases, the rhetorical association between climate change and extreme weather declines precipitously among Republicans while remaining consistent among Democrats. We also show that Republicans more closely associate renewable energy with policy investment in districts with minimal reliance on fossil fuels for employment; conversely, Democrats show no variation in their rhetoric across various levels of fossil fuel reliance. 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 for possible future pro-climate coalitions within the U.S. Congress.

Data

To assess politicians' positions on climate change, we examine policy platforms scraped from the campaign websites of U.S. House candidates who ran in 2018, 2020, or 2022.[1] We examine campaign websites for several reasons. First, policy debates about climate change are infrequent in Congress and are especially rare among Republicans.[2] Discussions of climate policy happen more frequently in congressional elections, thus providing 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 change 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 main venues elites use to communicate their policy stances to broad audiences (Sulkin, 2005). Moreover, unlike other sources for political text (e.g., social media posts), policy platforms from campaign websites are expressly policy-oriented and face no time or space restrictions (Druckman et al., 2009a), allowing candidates to emphasize every issue they view as important.

A wide literature finds that strategic candidates tailor policy positions to their electoral context. At the same time "hopeless" politicians are less responsive to such conditions and run for other reasons—not necessarily to win (Jacobson, 1989). We are interested in how strategic office-seekers tailor their rhetoric to district-level conditions and, therefore, constrain our analyses to "viable" candidates. Following recent work (e.g., Bonica 2020; Porter and Treul 2025), we consider candidates to be viable if they reported more than $75,000 in campaign receipts to the Federal Election Commission during their campaign.[3] Varying this cut-off threshold (+/- $25,000) does not

[1] See Appendix Section A and Porter et al. (2025) for a thorough discussion of data details and 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] See Appendix Section B for more discussion and descriptives about our selection criteria.

impact the main conclusions of our analysis. Of the 6,006 major party candidates in our sample, 2,748 (46%) were viable contenders with a campaign website that featured a policy platform.

Climate-Related Disaster Risk

We expect Republicans to attribute extreme weather events to climate change more closely in congressional districts with elevated costs of climate-related disasters. The main explanatory variable in this analysis of climate attribution is a measure of district-level expected annual losses (EAL) from climate-related disasters in 2020 dollars, based on the Federal Emergency Management Agency's National Risk Index (NRI).[4] 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). We employ FEMA's measure of EAL because it accounts for both the frequency and severity of natural hazards. Furthermore, EAL focuses on historic losses rather than projected future costs. Existing research finds that immediate risk may more likely trigger pro-climate action than will long-term, future risk (Gagliarducci et al., 2019). Importantly, this EAL measure 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 details regarding our approach and necessary methodological assumptions, see Appendix Section C.1.

Fossil Energy Employment Reliance

We expect Republicans to express greater support for renewable energy in districts with constituencies that rely less heavily on fossil fuels for employment. The main explanatory variable in this analysis is a district-level measure of employment carbon footprint (ECF) estimated by Graham and Knittel (2024). This measure captures employment vulnerability from energy sector decarbonization by quantifying the average metric tons of carbon dioxide equivalent per employee at the county level. Importantly, this measure captures the ECF of extraction (e.g., mining), produc-

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

tion (e.g., electricity generation), and consumption (e.g., heavy manufacturing) of fossil fuels.[5] We again employ areal-weighted interpolation to transform county-level ECF estimates into district-level estimates; see Appendix Section C.2 for details.

Method

We use a word embeddings approach to examine candidate rhetoric on climate change. Specifically, we evaluate variation in candidates' propensity to associate (1) climate change with extreme weather events, and (2) renewable energy with policy investments. To evaluate whether the strength of these rhetorical associations varies across different district conditions (i.e., climate-related disaster risk and fossil fuel reliance), we employ a word embedding approach. Unlike traditional "bag of words" approaches for computational text analysis, 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).

Semantic similarity between words can be calculated as the distance between embeddings (Kozlowski et al., 2019). We compute the cosine similarity between each anchor and keyword presented in Table 1, where values closer to 1 (-1) indicate a greater (lesser) likelihood of co-occurrence. We include multiple anchor 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. Following extant work (e.g., Garg et al. 2018; Kitagawa and Shen-Bayh 2024), we 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 reflect the average pairwise cosine similarity between all anchor phrases and keyword terms. Disaggregated results for pairwise cosine similarities are available in Appendix Figures E.4 and E.5. Our results are robust to a variety of alternative keyword terms (Appendix Figures E.8 and E.9).

To generate our word embeddings, we rely on a method that places à la carte (ALC) word

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

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

Analysis: Climate Change Attribution	
Anchor Phrases	**Keyword Terms**
`climate change; global warming`	`extreme, weather, catastrophic, crisis, flooding, storms, temperatures`
Analysis: Renewable Energy Support	
Anchor Phrases	**Keyword Terms**
`clean energy; renewable`	`investment, expand, encourage, prioritize, transition, future`

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

embeddings in a regression framework. 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` developed by Rodriguez et al. (2023) and implement the best practices for text pre-processing and hyper-parameter selection proposed by Denny and Spirling (2018).[6] Appendix Section D offers more details about text pre-processing, modeling procedures, and robustness checks. We estimate our models with a variety of district and candidate-level covariates. At the district level, we include the aforementioned measures of climate-related disaster risk (i.e., EAL) and fossil fuel reliance (i.e., ECF). We discretize these measures into terciles and interact them with candidates' party affiliations.[7] We also control for district partisanship using average two-party presidential vote share. At the candidate level, we control for gender, ideology as measured by Bonica (2024), incumbency, and PAC fundraising from pro-environmental groups or fossil fuel energy companies, as identified by OpenSecrets. We also specify year-fixed effects.

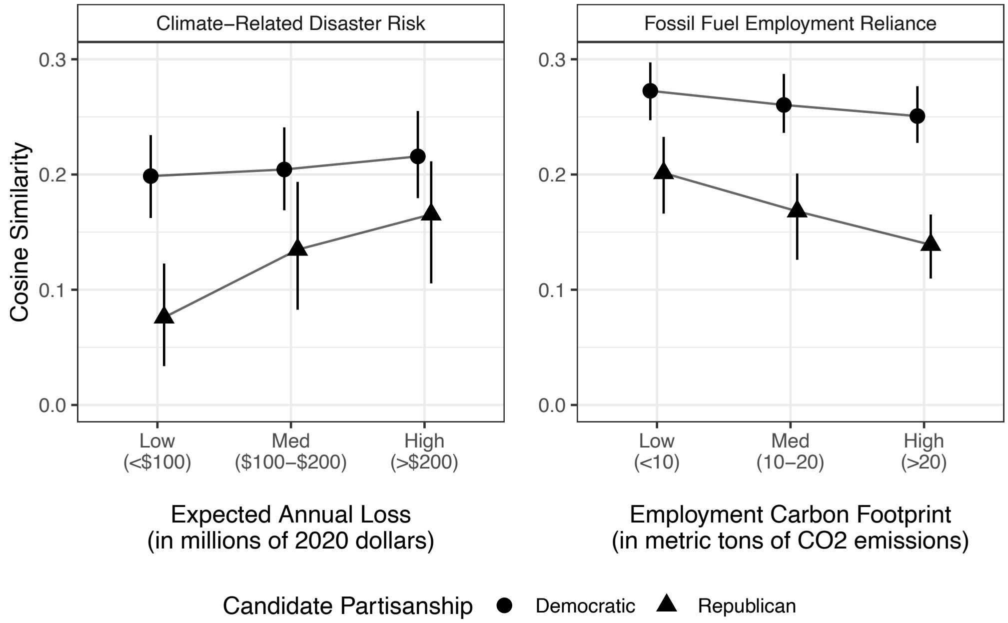
Results

Figure 1 displays the results of our analyses of climate-related disaster risk (left panel) and fossil fuel reliance (right panel). Point estimates reflect average cosine similarities between the predicted ALC embeddings for the anchor phrases and keywords from Table 1.

[6] Our ALC embeddings were generated with 6-word context windows and 300-dimensional vectors. Per Appendix Figures E.1 and E.2, our results are robust to alternative context window sizes (4, 8, 10, or 12). We employ GloVe pre-trained embeddings and a corresponding transformation matrix.

[7] Discretizing continuous measures simplifies our presentation of results, mitigates the risk of influential outliers, and accounts for small sample sizes in sparsely populated regions of the variable's range. Results are robust to various bin sizes (3, 5 or 10); see Appendix Figures E.6 and E.7.

Figure 1: Average Cosine Similarity Between Anchor Phrases and Keywords



Note: Plots reflect averaged cosine similarities between anchor phrases and keywords from Table 1. For disaggregated results, see Appendix Figures E.4 and E.5. 95% confidence intervals are bootstrapped 500 times using pre-trained GloVe vectors and ALC transformation matrix. The x-axis value of "High" indicates a value greater than or equal to the 66th percentile of EAL across all congressional districts; "Med" indicates a value greater than or equal to the 33rd percentile and less than the 66th percentile; "Low" indicates a value less than the 33rd percentile.

The left panel of Figure 1 shows that Democratic candidates generally more closely associate our anchor phrases `climate change` and `global warming` with keywords such as `extreme`, `weather`, `storms` and `temperatures`. Differences between average cosine similarities for Democratic and Republican candidates running in congressional districts with expected annual losses of less than or equal to $200 million are statistically significant ($p<0.05$); however, Democratic and Republicans running in high EAL districts (>$200 million) are statistically indistinguishable. Within party, Democrats exhibit little variation in their climate attribution rhetoric across congressional district-level EAL. Republicans, in contrast, more closely associate climate change with extreme weather when their district faces a heightened risk of costly climate-related disasters. Differences between average Republican cosine similarities for candidates running in low EAL congressional districts (<$100 million) and high EAL districts (>$200 million) are statistically significant ($p<0.05$). In Appendix Figure E.3, we replicate this analysis using hazard-specific EAL and find similar variation. We show that Republicans increasingly associate climate change and extreme weather in districts with elevated EAL from wildfires, heatwaves, and droughts, while Democrats are consistent in their rhetoric across all levels of hazard-specific EAL.

The right panel of Figure 1 displays the results of our renewable energy analysis. Across the full range of district-level ECF, Democratic candidates more closely associate `renewable` and `clean energy` with words such as `transition`, `encourage`, and `investment` than do Republicans. Differences between average Democratic and Republican cosine similarities are statistically significant ($p<0.05$). Republican candidates, by contrast, associate renewable energy and policy investment more closely in districts where constituents rely less heavily on fossil fuels for employment. Differences between average Republican cosine similarities for candidates running in low ECF congressional districts (<10 metric tons of CO_2e) and high ECF districts (>20 metric tons of CO_2e) are statistically significant ($p<0.05$).

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 template for scholars seeking to use word embeddings to analyze elite position-taking content in the context of congressional politics. Our findings suggest that intra-party variation in Republican House candidates' rhetoric on climate change is 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 factions of the Republican Party than others. A cohesive Democratic Party might, therefore, find bipartisan allies in districts that experience more frequent and severe natural hazards related to rising temperatures. Similarly, Republican politicians from districts with lower fossil fuel reliance may be more likely to support legislation advancing clean energy.

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Online Appendix for: Communicating on Climate Change

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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 because their widespread adoption makes them broadly 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 positions on campaign websites because these sites serve as a "hub" for campaign information. These sites are also visited frequently by electoral stakeholders like constituents and potential donors (Druckman et al., 2009b; Herrnson et al., 2019), so it behooves candidates to paint a complete picture of themselves on their websites. By contrast, candidates' use of other online platforms like social media depends greatly on their political sophistication (Lassen and Brown, 2011), partisanship (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 whether candidates' social media usage reflects the broader policy focus of their campaigns, whereas such uncertainty does not exist concerning position-taking on websites. Existing work compares candidates' stances on their campaign websites and 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 elite communication in contemporary congressional elections by Porter et al. (2025). To collect text data from candidate campaign websites, Porter et al. (2025) first identified the names of all major party candidates running in 2018, 2020, and 2022 using candidate filings with the Federal Election Commission (FEC), state-level elections websites. Using this list of names, they identified the campaign website URLs for all candidates in a given election year by following links from online repositories like Politics1.com, visiting candidates' social media pages, and conducting simple Google searches. Of the 6,006 congressional candidates who ran between 2018 and 2022, about 87% had a campaign website. A team of research assistants cataloged campaign website text for each election. To ensure consistency, text was collected during the week 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. Then, using a Qualtrics survey, RAs indicated 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 and paste the entirety of text contents from campaign platforms into Qualtrics. Some candidates who adopted a campaign website did not outline any policy positions on their site. Of those candidates who had a campaign website, about 85% (n = 4,681) included a campaign platform.

B Units of Analysis

Our analyses are interested in capturing the strategic position-taking behavior of U.S. House candidates. However, not all candidates running for Congress behave strategically. Several studies find that a sizable proportion of congressional candidates pursue non-political and non-electoral goals; for instance, seeking material benefits or advance their professional careers (Leuthold, 1968; Maisel, 1986; Canon, 1990; Maisel and Stone, 1997). Candidate motivations have downstream consequences on strategic campaign behavior. For instance, 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 ambivalent toward electoral context and do not tailor their position-taking behavior; these individuals are not necessarily running to win. Because we are interested in examining how a candidate's district context impacts their climate change positions, we only analyze "viable" 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). Recent work, however, finds that prior officeholding experience no longer consistently predicts candidate quality or campaign professionalism (Porter and Treul, 2024). Following this research, we rely on campaign fundraising as a barometer for candidate viability.

To identify viable candidates, we examined the fundraising potential of all candidates who filed with the Federal Election Commission (FEC). In our time series, the median incumbent raised $1,705,609 in a single campaign cycle (primary and general election), while the median non-incumbent raised $141,664.. The median non-incumbent candidate who lost their primary raised $86,911. Based on this, we selected the threshold of $75,000. Variations in this cut-off threshold (e.g., $0, $25,000, $50,000, or $100,000) do not impact the substantive takeaways of our main paper analysis but increase statistical uncertainty.

Of those 6,006 major party candidates who ran for the U.S. House of Representatives between 2018 and 2022, a total of 2,748 (46%) 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 2,826 candidates were excluded from our analyses for not qualifying as "serious." From those remaining candidates, another 432 candidates were excluded because did not have a campaign website with a policy platform.

C Key Independent Variables

C.1 Measuring Climate-Related Disaster Risk

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 EAL estimates better capture 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 easily able to produce this kind of adjusted measure of FEMA's NRI.

We use a method for areal-weighted interpolation to transform FEMA's census tract estimates of EAL to our target unit of aggregation (i.e., congressional districts). 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 intersection with congressional districts.[8] Areal interpolation assumes 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).[9] 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.2 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

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

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

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.

C.2 Measuring Fossil Energy Employment

Graham and Knittel (2024) estimate the extent of community vulnerability to the employment impacts of the "green" energy transition. The authors analyze eight major sectors: agriculture, manufacturing, commercial sectors, construction, coal mining, oil and gas extraction, other mining, and fossil-fuel power generation, which accounts for 86% of total U.S. employment and 94% of U.S. carbon emissions. The lowest unit of aggregation available for these estimates is the county level. We employ the same areal interpolation approach described above to aggregate counties into congressional districts. We rely here on spatially intensive interpolation because data are average rates rather than dollar amounts. We specifically employ Graham and Knittel's 2024 estimate for the average metric tons of carbon dioxide equivalent per employee at the county level. The authors do not provide year-wise longitudinal estimates at this time. 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.

D Text Analysis

D.1 Pre-Processing

In our text pre-processing, we follow the best practices proposed by Denny and Spirling (2018) as well as those pre-sets in the R package `context` from Rodriguez et al. (2023). In tokenizing our corpus, we remove punctuation, symbols, numbers, and separators. 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 in 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 between extreme weather events and climate change. According to 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 measuring climate change attribution (e.g., Hai and Perlman 2022; Lahsen et al. 2020). To include more specific references to the physical impacts of climate change, we additionally included the terms “flooding”, “storms,” and “temperatures.” Finally, to underscore the urgency of climatic change threat, we include the terms “catastrophic” and “crisis.”

To select our investment keywords, we adopted a similar approach. The terms “investment” and “expand” 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 terms “prioritize” and “transition” are 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, we included the terms “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 corpus texts. 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.8 and E.9. 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 E.1 and E.2 we demonstrate that our results are robust to different window length specifications.

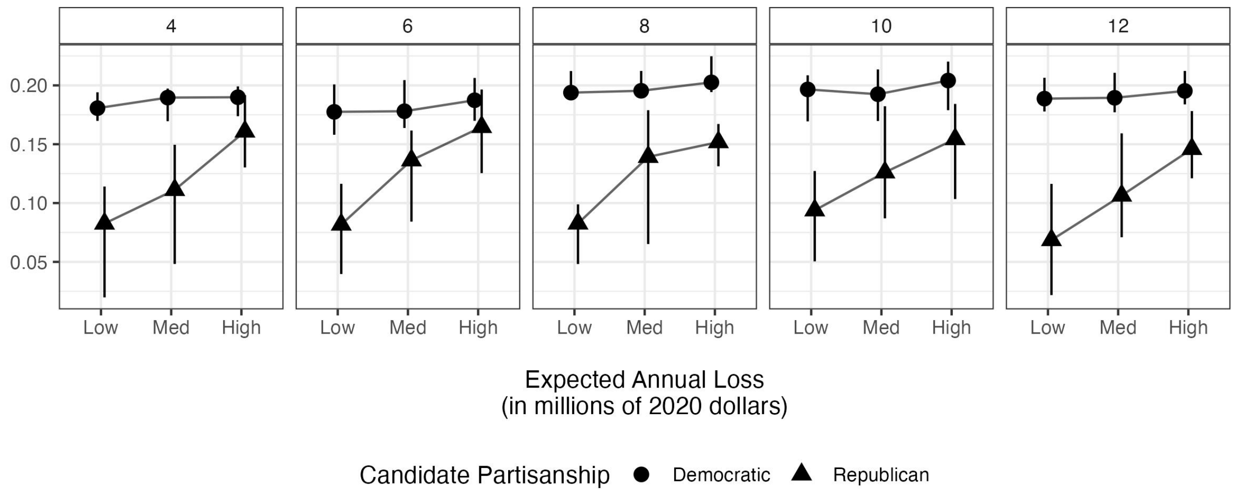
We estimate two separate embedding regressions, one for our climate-related disaster risk analysis and one for our fossil fuel employment analysis. In our disaster risk analysis, we control for district-level threat and those controls outlined in the main body of the paper. In these regressions, we interact with party with our main explanatory variable. Additionally, as discussed in the main paper, we discretize our primary independent variables into five equal categories (quintiles). This approach allows for non-linearity the relationship between rhetoric and key explanatory 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). Varying the number of categories (3,5, or 10) produces substantively identical results.

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).

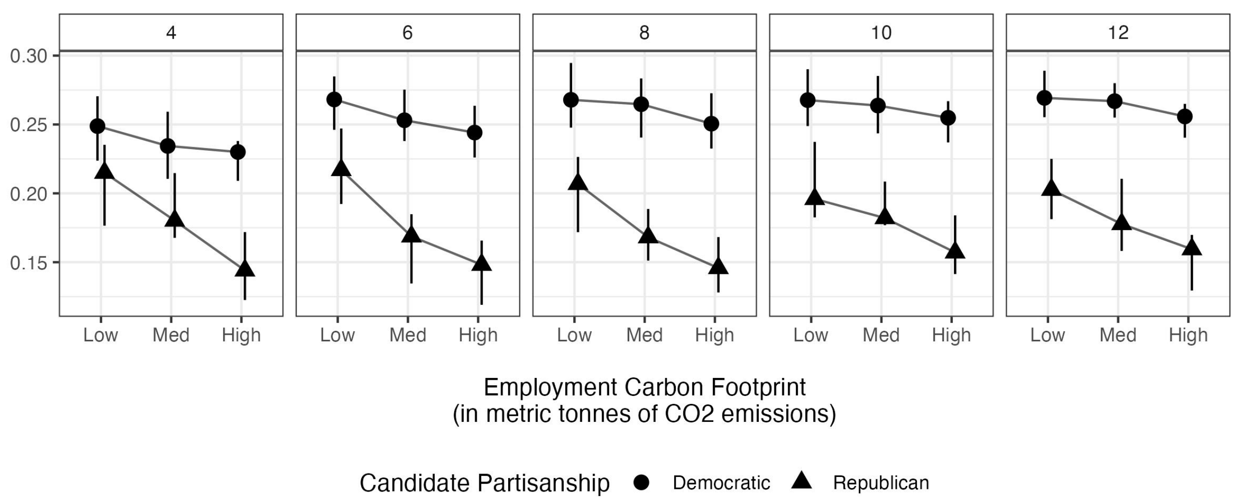
E Supplemental Tables and Figures

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



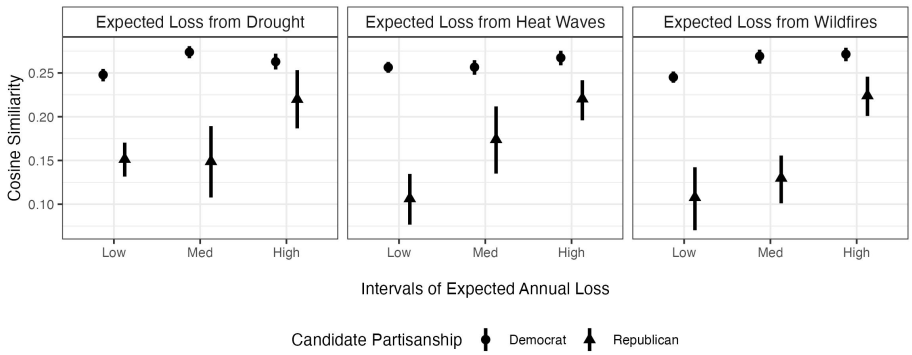
Note: ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as the left panel of Figure 1 in the main paper, with the exception of varied context window length.

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



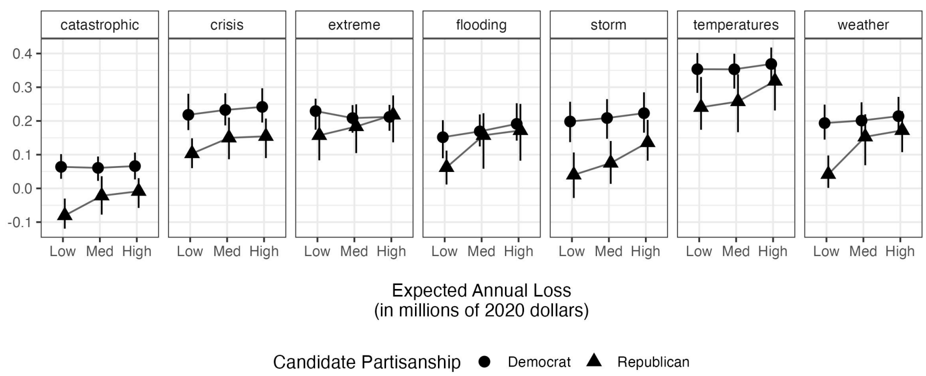
Note: ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as the right panel of Figure 1 in the main paper, with the exception of varied context window length.

Figure E.3: Cosine Similarity Between "Climate Change" and "Global Warming" Focal Phrases and Extreme Weather Keywords for Individual Disaster Events



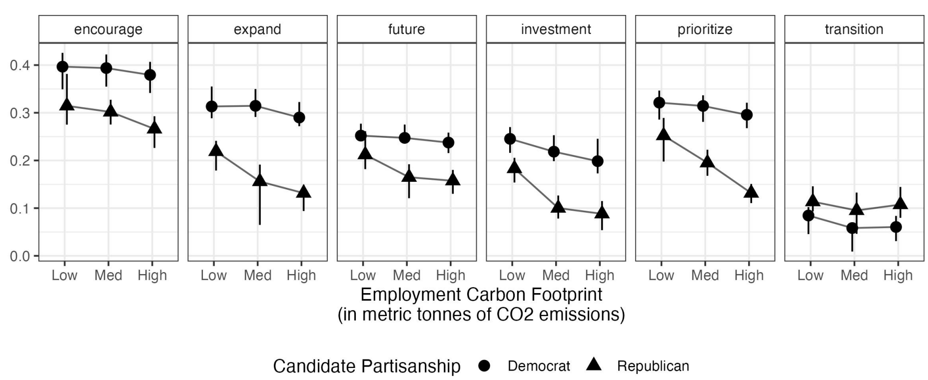
Note: Text pre-processing follows identical procedures employed in main paper analyses. Confidence intervals of 95% are produced through 100 bootstrapped simulations.

Figure E.4: Cosine Similarity Between "Climate Change" and "Global Warming" Target Phrases for Extreme Weather Keywords (Disaggregated Results)



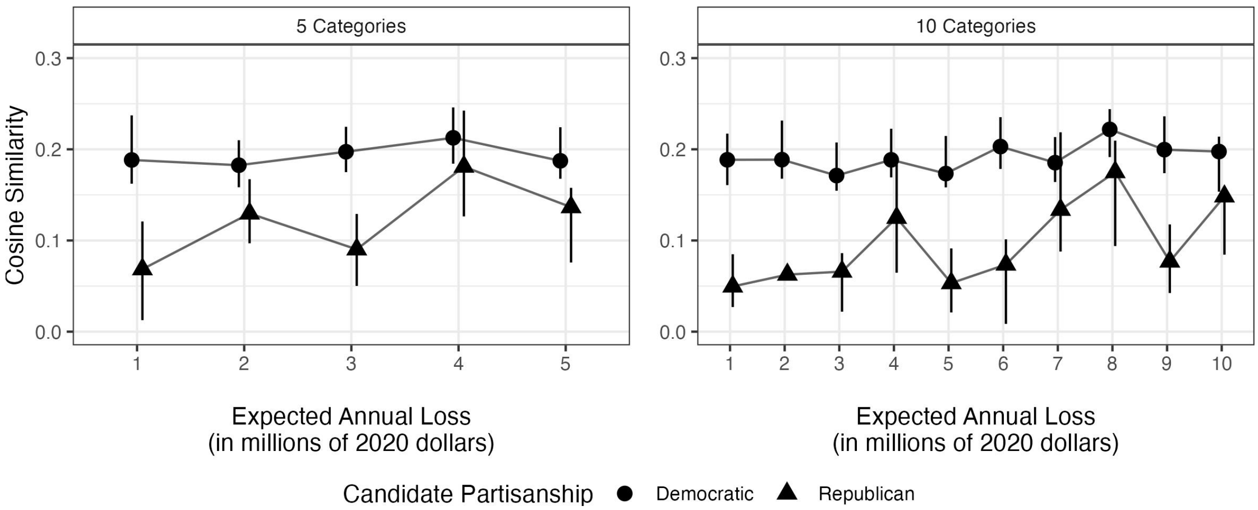
Note: Cosine similarities reflect individual target-keyword comparisons from Figure 1, left panel of the main paper.

Figure E.5: Cosine Similarity Between "Renewable" and "Clean Energy" Target Phrases and Investment Keywords (Disaggregated Results)



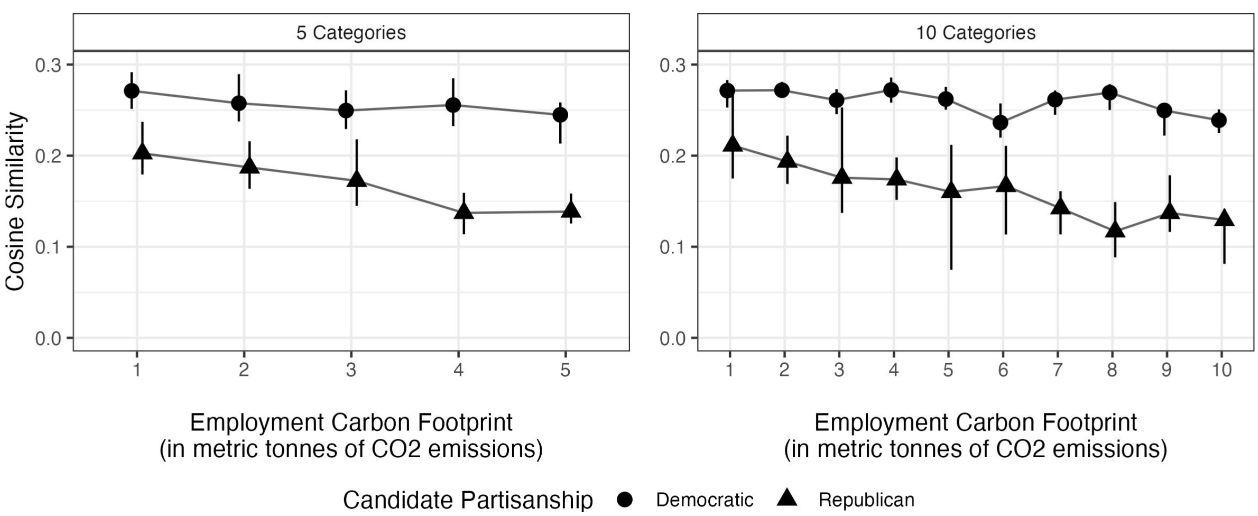
Note: Cosine similarities reflect individual target-keyword comparisons from Figure 1, right panel of the main paper.

Figure E.6: Cosine Similarity Between “Climate Change” and “Global Warming” Target Phrases and Extreme Weather Keywords (Varied Bin Sizes)



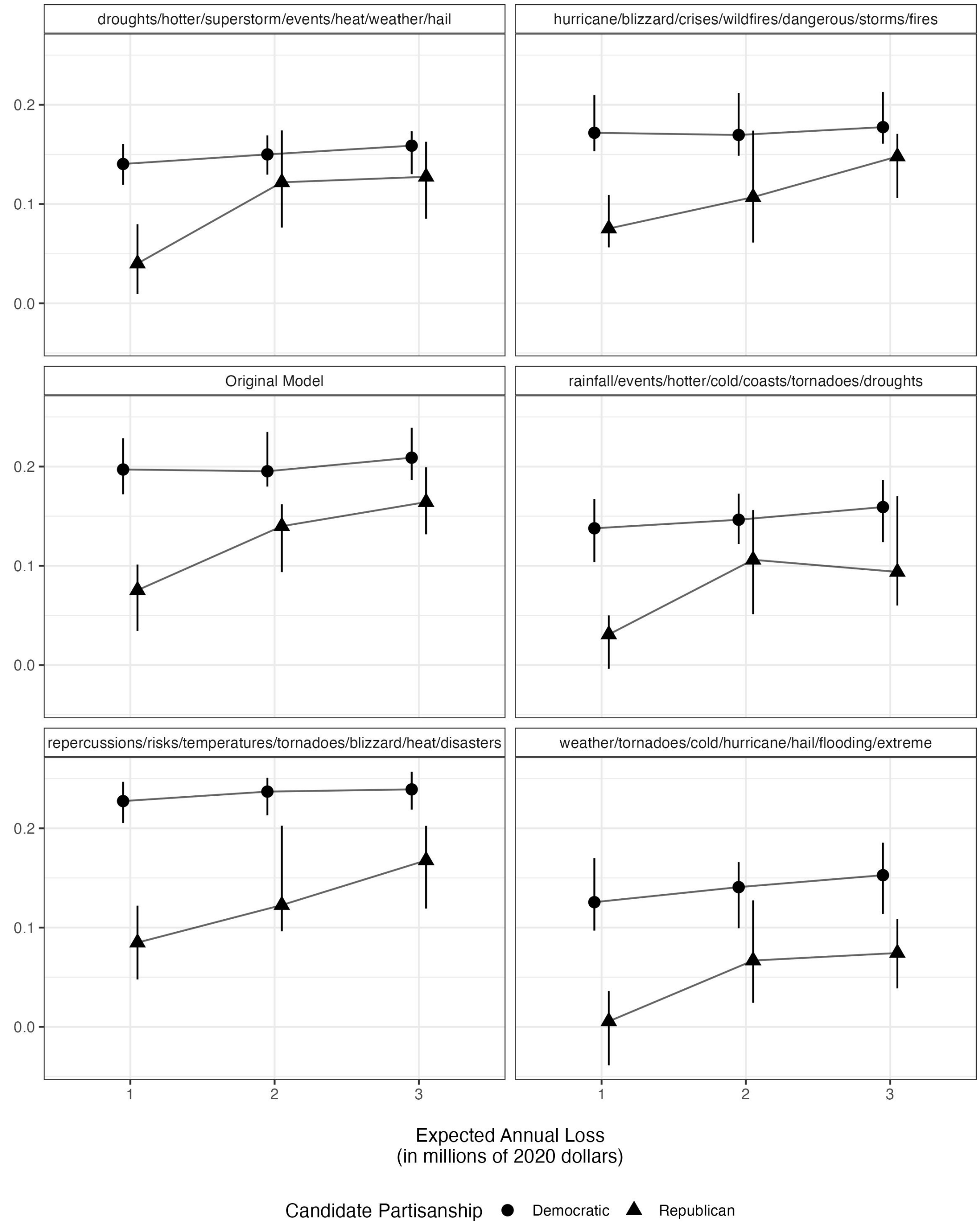
Note: ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as the left panel of Figure 1 in the main paper, with the exception of varied bin sizes.

Figure E.7: Cosine Similarity Between “Clean Energy” and “Renewable” Target Phrases and Investment Keywords (Varied Bin Sizes)



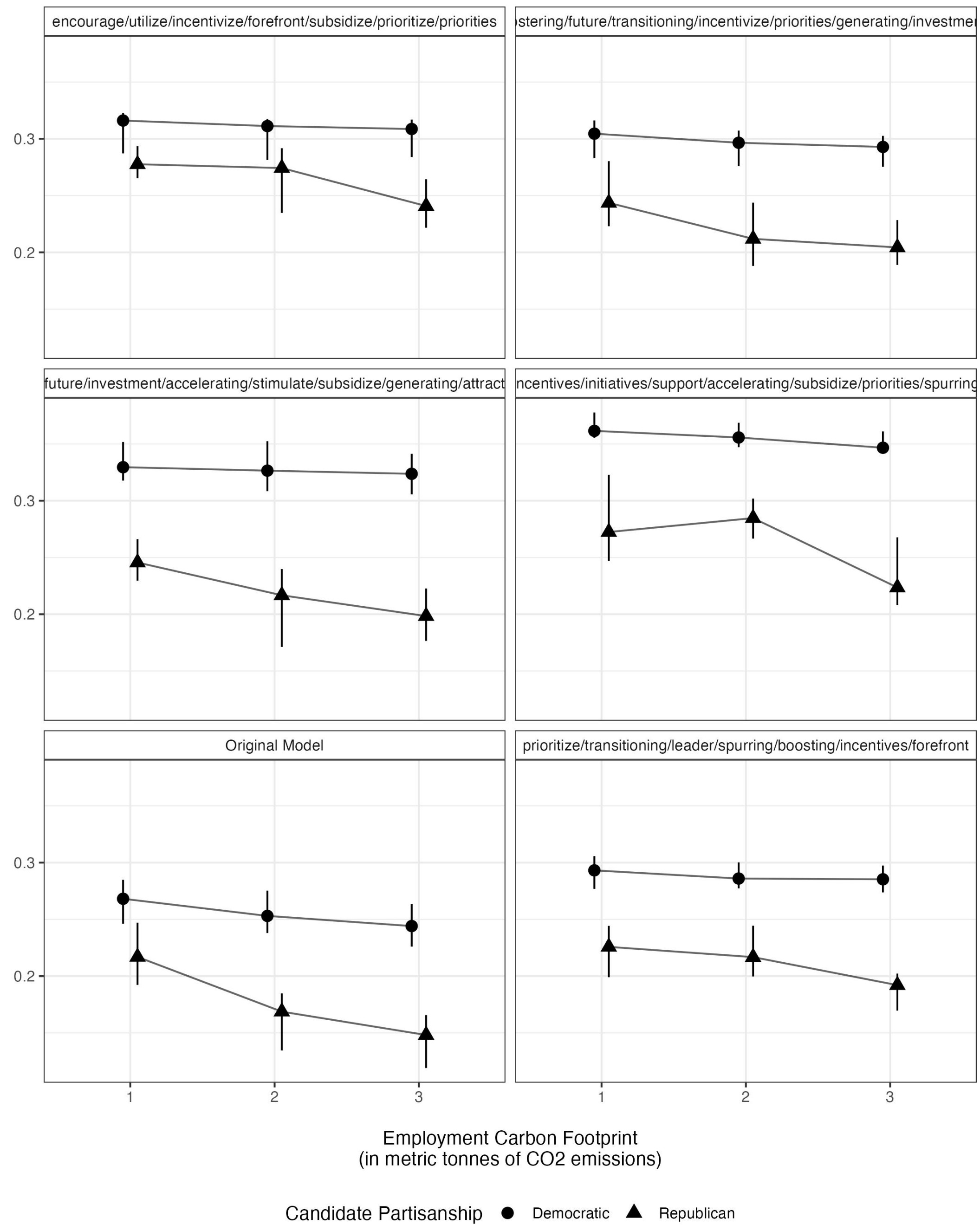
Note: ALC embeddings estimated using the same pre-processing steps and hyper-parameter specifications as the right panel of Figure 1 in the main paper, with the exception of varied bin sizes.

Figure E.8: 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 the left pane of 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, flooding, storms

Figure E.9: 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 the right panel of 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. data clearly shows that climate change increases the risk and intensity of extreme weather. 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 the catastrophic outcomes of climate change mandate that we cut carbon pollution resilient against catastrophic wildfires. For climate change advocates the amount of CO2
weather	global warming would produce more severe weather events such as increased flooding 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 every year has seen record-breaking temperatures. Climate change presents a real threat 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 jobs training, creating incentives for clean energy innovation, encouraging companies to legislation that would extend and expand clean energy incentives, like permanently
encourage	support policies that encourage the growth of clean, renewable energy and discontinue 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 He’ll work to restore funding for clean energy investment, ensure the United States honors 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. Let’s prioritize sectors (e.g. renewable energy) with the highest potential for job creation. 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. threat facing humanity, and clean energy jobs are the future of Indiana’s economy sweeping environmental omnibus bill, (S.2545 An Act to promote a clean energy future)

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