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LETTER

Echo chambers in climate science

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Abstract

To date, echo chambers in American climate politics have been found to focus on the climate-related policy instrument that is under review. In this paper, we explore how echo chambers change over time, integrating data collected on the federal climate policy network after the first 100 days of the Trump Administration had passed with data collected during two periods during the Obama Administration. We employ Exponential Random Graph (ERG) models to test for the similarity and differences over time in the top policy actors working on the issue during each time period. We then compare the newer findings from 2017 to previous work on data from 2010 and 2016. We find that echo chambers continue to play a significant role in the network of information exchange among policy elites and in the adoption of new information sources over time. In contrast to previous findings, however, where echo chambers centered on specific policy instruments—a binding international commitment to emission reductions or the Obama Administration's Clean Power Plan—opinion regarding whether or not climate change is caused by humans (i.e. is anthropogenic) has become the central organizing force behind echo chambers in the US climate policy network. These results provide new empirical evidence that ideological polarization drives the selection of expert information in the debate around climate politics. Moreover, our results show how misinformation diffuses among political elites working on the issue of climate change.

Political polarization continues to be a challenge to environmental policymaking in the United States [1, 2]. Even with the overwhelming consensus by scientists that the climate is changing due, in part, to human activity [3, 4], public opinion about climate change has been found to be strongly associated with political ideology [5–7]. In recent months, however, concern about the issue has grown [8]. Research has found that 'climate denial'—challenges to the overwhelming scientific consensus around climate change—has been effectively utilized by the so-called climate countermovement as a means to block political progress [2, 9–11, see also 12]. In particular, this research has focused on the diffusion of disinformation to the public by organizations that received corporate funding.

At the same time, scholars have taken advantage of innovations in computational social science to provide insights into 'exactly how connections among people create societal trends' [2, 13–15]. Employing computational research methods, this paper looks at how climate denial has become a central organizing force in climate politics under the Trump Administration. In contrast to the research on the climate countermovement, this study looks at information diffusion among policy actors engaged in climate decisionmaking in the US. Building on research that finds echo chambers—patterns of similarity regarding where policy actors get their expert information—in American climate politics [16, see also 17 for an example from Ireland] and that these echo chambers are focused on the relevant policy instrument under review at the time of the research [18], we provide evidence to demonstrate how echo chambers change over time. Specifically, this paper reports the results of analysis of how echo chambers in American climate politics have reoriented themselves around challenges to the science of climate change before and after the 2016 election. To that end, we analyze a new dataset collected from the most central policy actors involved in the US climate policy network in 2017—100 days into the Trump Administration. We show that, since the first wave of data collection in 2010, climate skepticism, specifically around whether climate change is anthropogenic, has grown among policy elites and that this growth is reinforced by actors restructuring their network to take advantage of echo chambers. A corresponding growth has been documented in conservative think tanks [19], public communications by fossil fuel companies [20], and private philanthropy [21]. However, this paper is the first to document the same patterns at work among political elites.

To understand how climate-related echo chambers have changed during the Trump Administration, we examine the 'sources of expert scientific information about climate change'[3] for members of the climate policy network in the United States to understand information diffusion. Below, we briefly describe the data collected, operationalize our understanding of echo chambers using social network methods, and apply Exponential Random Graph (hereafter, ERG) models to test for the presence and significance (relative to tie formation) of such echo chambers among members of the US climate policy network. For a full discussion of the policy network approach, which uses policy actors at the unit of analysis, see the work of Knoke [22] and, for a more recent perspective, see Leifeld and Scheider [23].

This research analyzes data collected through a survey of the top policy actors working on the issue of climate change in the United States. As described in much more detail in the SI Appendix, the survey includes attitudinal questions about the policy actors' perspectives on numerous salient issues related to the subject of climate change, as well as where each policy actor goes (within the network) for 'expert scientific information about climate change.' Data were collected in 2010, 2016, and 2017. The period of data collection spans 3 Presidential terms and 4 sessions of the US Congress.[4]

As one might expect, our sample changes greatly over the span of the period of study (2010–2017). In this paper, we first compare static analyses of the full data sets from three waves of data collection over this 7-year period (n of 64, 50 and 61 respectively) and then we present temporal analysis of the longitudinal sample. Although each wave of data collection yielded a response rate above 55%, the turnover inherent to studying political elites working on an issue over time means that our reduced longitudinal sample of policy actors that responded to all three waves of the survey is 13. This small number is due to the fact that the central actors in the network changed as organizations, associations and companies became less involved in the issue, as well as due to turnover in political offices over this period of time. While methods for temporal network analysis with missing data are being developed, the standard (albeit limited) approach is to eliminate respondents that are not common across waves [24, 25, for an example of the most recent efforts to model changing node sets, see 26]. By comparing the larger static networks to the smaller temporal findings, we are able to build on the strength of the larger samples to look at both how ties change over time and how these changes are reflected in the broader community.

Respondents to our survey represent the nodes in the network. The policy actors who are identified as sources of the respondents' expert scientific information on climate change are the edges in the network. For example, when actor *B* states that they received information from actor *A*, there is a directed tie from *A* to *B*. This relationship is depicted in figure 1(a). We use two attitudinal questions as node attributes. Policy actors' responses to: *Human activities are an important driver of current global climate change* (referred to as Anthropogenic) and *There should be an international binding commitment on all nations to reduce GHG emissions* (referred to as Binding and the policy instrument focused on in previous research on echo chambers [16]). For details about the sampling, the survey, and how data were collected, see Supplemental Information.

Analytic approach

Following previous literature, we employ an ERG modeling approach for the static samples and a temporal ERG model for the longitudinal samples. In these models, the network is the dependent variable and different network motifs are parameterized as sufficient statistics [27]. This approach incorporates the many basic building blocks of social networks, as well as our operationalization of an echo chamber, which combines information diffusion through transitive triads with homophily. In other words, echo chambers exist when there is both multi-path transmission of information and agreement among all parties connected [for details, see 16]. The ERG model enables a statistical comparison of the echo chamber (figure 1(h)) controlling for other terms in the model including separate terms for heterophily (see figure 1(g), parameterized as anti-homophily) and the chamber itself (figure 1(d)). These terms are shown in figure 1. Additionally, we control for known network

[3] This wording is taken directly from our survey of policy actors.

[4] See supplementary information for additional details of data collection, cleaning, and the handling of missing data.

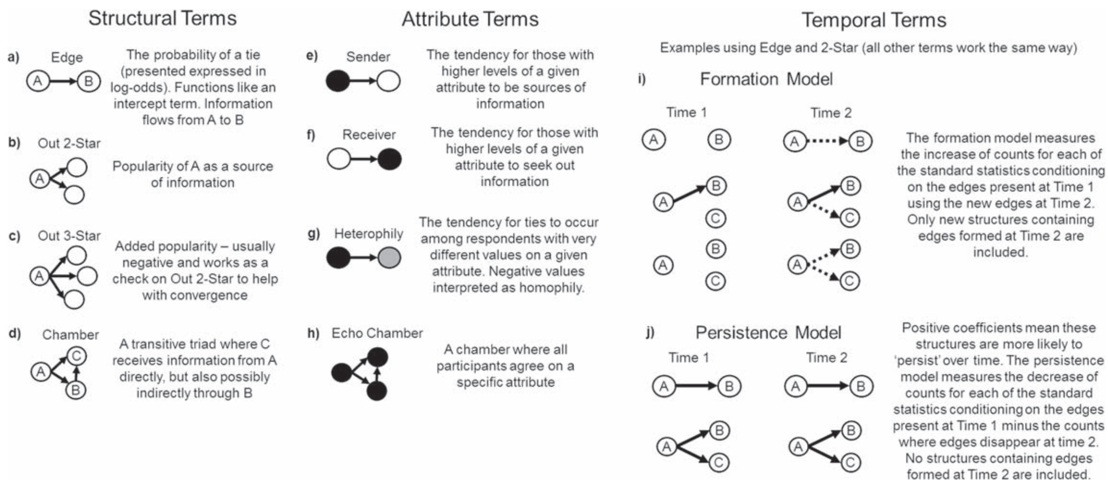

Figure 1. Terms used in ERG (left and center) and STERG Models (right).

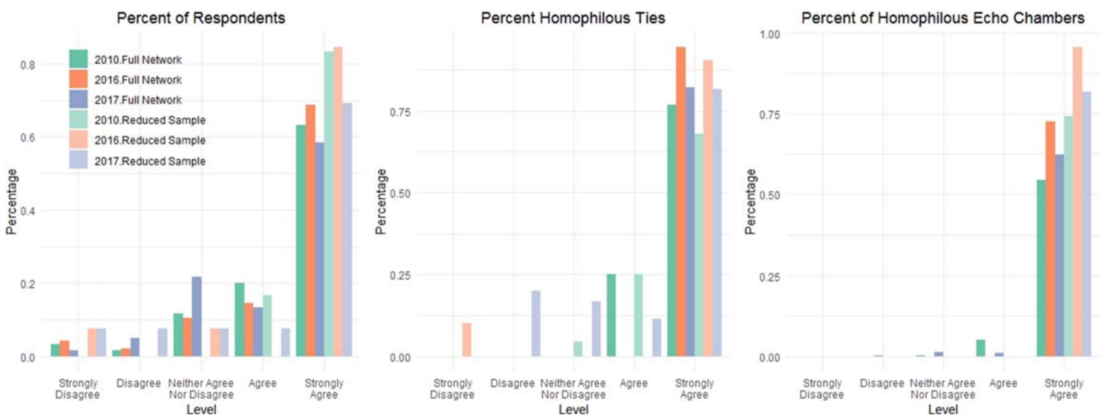

Figure 2. Description of Attitudinal Data for Full Sample and Reduced Longitudinal Sample by year.

mechanisms of popularity (through a combination of the terms in figures 1(b) and (c)), as well as the differential tendencies of certain actors to send and receive ties (figures 1(e) and (f)).

With the new data from 2017, we are able to model temporally the longitudinal sample using a Separable Temporal ERG Model [28]. In the temporal models, we use the same terms, but we focus on predicting what ties are added (formation model shown in figure 1(i)) and what ties persist (persistence model shown in figure 1(j)). This type of model is common in longitudinal network analysis [see 29, 30] and has been used previously to look at policy networks [31]. This research has found that, in some cases, that transitive triads (our chamber) and homophily (our echo) are associated with the formation of ties in networks over time [32].

Results

Distributions for the Anthropogenic attitudinal question (left), the density of ties among people who agree (ie the percent of sent ties that are homophilic) (center), and the percentage of chambers that are echo chambers (ie information is being diffused directly and indirectly among policy actors who agree on an attitudinal question) (right) in both the full (solid lines) and reduced longitudinal samples (dashed lines) are presented in figure 2. In the first panel, we see a great deal of similarity over time, as well as between the full and reduced samples. In fact, more than half of each static sample strongly agrees that human activities are an important driver of current climate change (63%, 69%, and 58% respectively of the full samples). It is worth noting that the lowest level of agreement is in 2017 when there was an increase in respondents who strongly disagree, disagree, or took a neutral position neither agreeing nor disagreeing with this attitudinal question. We see similar distributions in the percentage of homophilic ties and echo chambers—most of the action is concentrated around those who 'strongly agree' that climate change is Anthropogenic with slightly varying levels. The most

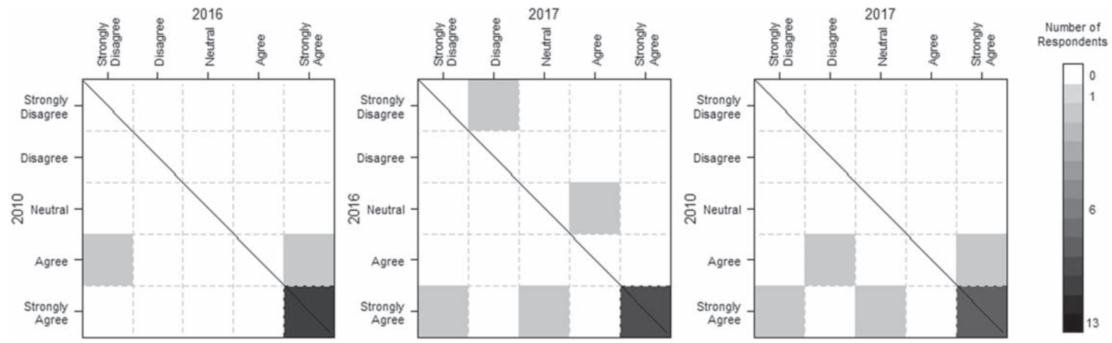

Figure 3. Heat maps for change in anthropogenic response for longitudinal sample.

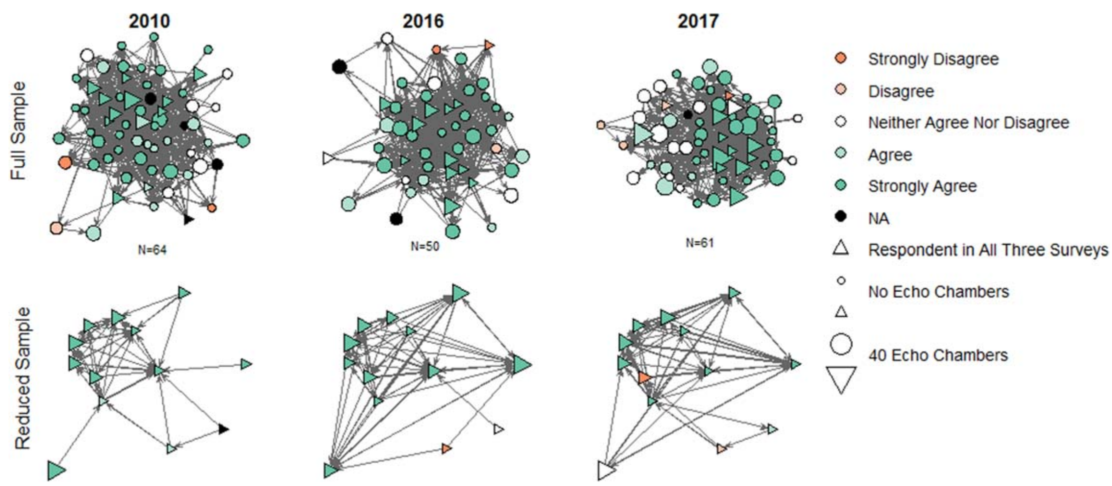

Figure 4. Network diagrams for static samples (top) and reduced longitudinal samples (bottom) in each year. Placement of nodes for reduced samples are identical in each year.

significant difference between the full and reduced samples is in the number of echo chambers among those who strong agree on Anthropogenic.

Figure 3 Presents the change in responses to the attitudinal question for the 13 respondents who are the same in each year. We see that the Anthropogenic responses stay relatively similar over time, with the majority remaining in the 'Strongly Agree' category. Of the 13 policy actors included in the longitudinal responses, 3 (23%) respondents changed their position on Anthropogenic between 2010 and 2016 and 4 (31%) from 2016 to 2017. In the heat maps in figure 3, squares along the diagonal represent individuals that did not change their opinion. Changes below the diagonal line indicate less agreement with the statement that climate change is Anthropogenic, and changes above represent more agreement. While the changes from 2010 to 2016 and 2016 to 2017 are mixed, the overall trend from 2010 to 2017 (figure 3, panel 3) shows an overall decreasing trend. In other words, respondents changed their views to be less supportive of the science that climate change is anthropogenic.

Figure 4 presents the networks of the full sample and the longitudinal samples over time. Nodes are colored based on the respondent's position on the Anthropogenic question. Although there was a limited number of changes in the views on Anthropogenic, there was much higher turnover in network ties during this time, which, as previously stated, spans 3 Presidential terms and 4 sessions of the US Congress. Only 20 (47%) of the 43 ties in the 2010 reduced longitudinal sample remain in 2016. In contrast, 38 (69%) of the 55 ties in the 2016 sample remain in the 2017 wave, which also has 22 additional ties. Only 15 ties, however, are common across all 3 samples. In other words, there is far more change in the network ties than in the attitudinal data on the question of whether humans are an important driver of climate change. It is likely that we find more preservation of ties in the change from 2016 to 2017 than 2010 to 2016 due to the difference in interval periods, but the amount of change between our later samples is still quite high. Because the Anthropogenic variable is so stable (as illustrated in figures 2, 3, and 4), it is a challenge to model change in attitude over time. Given the limited changes over time in these raw statistics, we now turn to ERG models to examine the changes in the network structure and interactions among these measures.

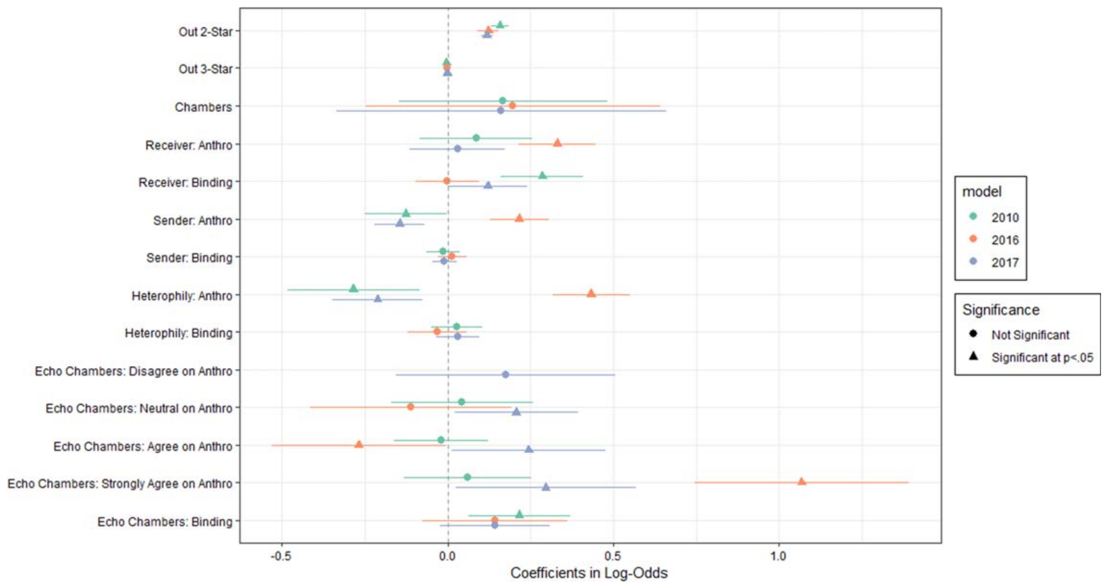

Figure 5. ERG models for static samples. Coefficients shown as circles (not significant) and squares (significant at $p < .05$) with lines as 95% confidence intervals.

Static models

Static models for each year are shown in figure 5. The 2010 and 2016 models are similar to those presented in previous papers [16, 18]. Previous work also found new structures to form around the Clean Power Plan in 2016 [18]. Since President Trump dismantled the Obama-era climate policy [33, 34], respondents in the 2017 survey were not asked about this policy instrument. We see a shift in the significant echo chamber terms from support for an international binding commitment (Binding) in 2010 to human activities being an important driver of climate change (Anthro) in 2016 and 2017. The coefficient for Binding echo chambers is still positive after 2010, but is no longer significant. After initial models showed significance for echo chambers in Anthro (see SI figure S1 is available online at stacks.iop.org/ERC/1/101003/mmedia for this model), we divided the attribute based on level of agreement to see whether these echo chambers occurred in each category. We see significance for 'Strongly Agree' echo chambers in 2016 and 2017, but additionally echo chambers for 'Agree' and 'Neither Agree nor Disagree' is significant in 2017. This finding provides evidence that there is an increasing level of polarization around whether human activities are an important driver of climate change.

Beyond this finding for echo chambers, we see that the 'echo,' or homophily in Anthro, has also increased. In 2010, there was a negative and significant finding for heterophily in the models (which is interpreted as similarity among policy actors, or homophily). The coefficient switches to positive and significant in 2016. Our interpretation of this result in light of the significant term for Anthro echo chambers is that, while there is a tendency for echo chambers around Anthro to form, outside of those echo chambers, other ties among actors are unlikely to be homogenous on Anthro. About a year later, 100 days into the Trump Administration in 2017, the results are different. In 2017, not only are these echo chambers likely to form, but outside of these chambers, homophilous ties are also more likely. Taken together, these two findings demonstrate an ever increasing tendency towards information diffusion only among policy actors who agree about the science of climate change. Our results show that, as perspectives on human activities as a driver of climate change become more diverse among these policy elite, homophily is reinforced structurally with echo chambers. In other words, these findings provide evidence of increasing polarization around the question of whether climate change is anthropogenic. This finding is particularly robust for the categories where we have more than 3 observations (disagree is positive but not significant most likely due to the limited number of observations).

Temporal models

We include both formation and persistence models in the temporal analysis shown in figure 6. The formation model predicts new ties at time t+1 given the ties at time t (figure 1(i)). The persistence model predicts which ties remain at time t+1 given the ties at time t (figure 1(j)). Across all of the temporal analysis, only one term is statistically significant: Anthro echo chambers in the formation model. This finding indicates that ties are much more likely to be added in both 2016 and 2017 if they contribute to the number of echo chambers around the question of whether climate change is anthropogenic in the network. While the data permitted us to model echo

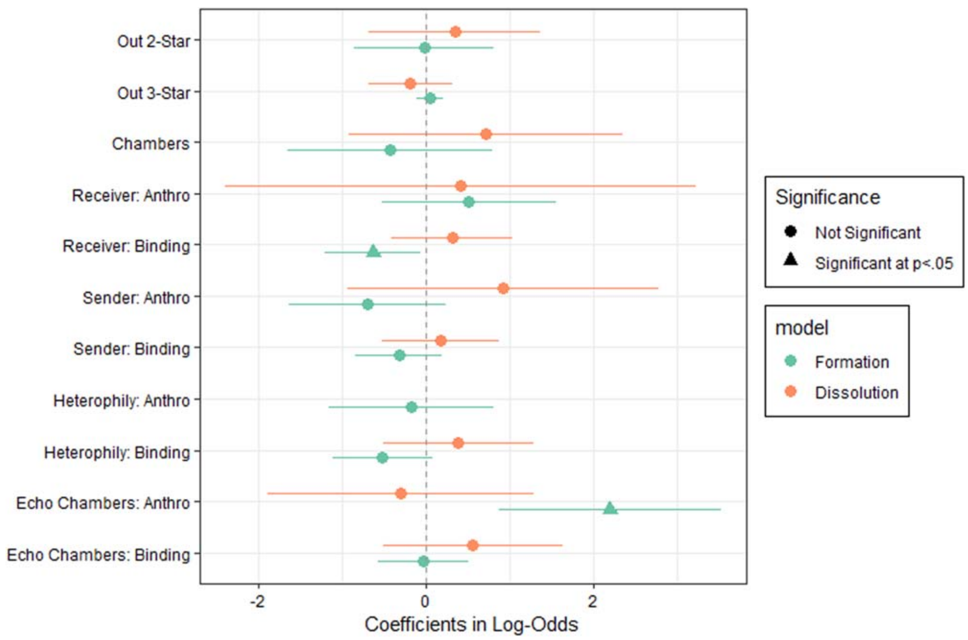

Figure 6. Separable Temporal ERG models for reduced longitudinal samples. Coefficients shown as circles (not significant) and squares (significant at $p < .05$) with lines as 95% confidence intervals.

chambers at different levels of agreement with Anthro in the full networks, too few respondents held views other than 'Strongly Agree' in the reduced samples to model the other categories.

In addition to the significant finding for echo chambers among those policy actors who 'Strongly Agree' that humans are a driver of climate change in the formation model, we also see a negative tendency for those who more strongly support Binding to name others as information sources (and, thus, be the receiver of this information). This finding is congruent with what one might expect since attention to an international policy instrument decreases over time; those most committed to it are looking outside their usual sources for other information. Finally, we also find clear differences between the formation and persistence models. The significant terms in the formation model are not replicated in the persistence model, and the magnitude of the coefficients have opposite signs. This finding indicates a separation between the network mechanisms responsible for the formation of ties and those that govern the dissolution of ties in this network. In other words, those network mechanisms that predict the formation of ties play no role in predicting what ties will persist or be dropped from the network.

Discussion

Overall, this paper provides clear evidence that echo chambers in American climate politics have reoriented themselves around challenges to the science of climate change. The static models show the increasing importance of beliefs about the science of climate change in our samples of the US climate policy network. Small but increasing numbers of respondents cast doubt on whether humans were an important driver of climate change across the three waves of data collection. We see a shift from a lack of significance around echo chambers (albeit with significant homophily) in 2010, to positive and significant echo chambers around 'Strongly Agree' but negative and significant echo chambers around 'Agree' in 2016 with significant heterophily. In 2017, the combination of both positive significant echo chambers around Anthro at the levels of 'Strongly Agree', 'Agree', and 'Neither Agree nor Disagree,' as well as a tendency for homophily above and beyond the echo chambers indicates that there was a change and reordering of the network structure to increase the information flow among policy actors who hold the same perspective on the science of climate change.

The results for the reduced longitudinal sample reinforce the findings from of our analysis of the static networks: Anthropogenic echo chambers have become the chief mechanism that is correlated with new tie formation over the 7-year period. While the ERG models are not causal, given the relative stability in the Anthropogenic attitudes and the clear preference for formation of echo chambers, these findings indicate a change in network configuration to reflect a greater tendency for selective polarization, rather than changes in attitude. Information gathering is less stable than opinion, and reinforcing echo chambers are likely to form among those policy actors with similar views even when none have changed their beliefs.

Our findings support the notion that the information network has switched from placing priority on the 'Binding Commitment' attitude to the question of 'Anthropogenic' over the 7 years of research on the US climate policy network. In 2010, the science of climate change was considered settled among the policy actors, but changes in the political climate (although not the scientific one) are clearly depicted in these results. Our analyses show that, while there is a subtle shift in policy elites' opinions about whether climate change is driven, in part, by human activities (depicted by the limited changes in opinion over the period of this study), these changes are complemented and amplified by the shift among the ways that expert scientific information is being diffused throughout the network.

This paper substantially expands our understanding of the role that echo chambers play in information diffusion around the contentious issue of climate policymaking in the United States. By analyzing data collected from three waves of surveys that span 3 Presidential terms and 4 sessions of the US Congress, we show how echo chambers are reoriented over time. Although we find clear evidence of echo chambers around the question of whether or not climate change is anthropogenic, it is possible that they are the product of the polarized political environment of 2017. As the political environment changes and a policy instrument is once again proposed to address the issue of climate change, previous research would suggest that the echo chambers will once again shift [18].

Future research should continue to study the climate policy network to assess the durability of these echo chambers. In addition, while this paper analyzes temporal models to explore formation and persistence over time, data limitations make it impossible to model the role of different components of echo chambers. With additional data collected during a smaller increment of time, the sample would likely change less. With more attribute change and less network change, it would be possible to determine which comes first, the echo or the chamber. To understand political polarization and how information diffusion contribute.s to it, we must focus on these questions regarding the durability and formation of echo chambers over time

Materials and methods

Comprehensive information about the data collection, sampling, and statistical analyses are provided in SI Appendix. Code and data are now available at https://osf.io/zc9bf/?view_only=92765f5163604f9db7826fa68feb49cc.

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Author contributions

DRF secured funding, DRF and LJ designed research, DRF collected the data and oversaw the graduate research team that helped collect data, LJ analyzed data, DRF and LJ wrote the paper together.

The authors declare no conflict of interest.

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