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Anthropogenic climate change represents a global threat to human well-being[1–3] and ecosystem functioning[4]. Yet despite its importance for science and policy, our understanding of the causes of widespread uncertainty and doubt found among the general public remains limited. The political and social processes driving such doubt and uncertainty are difficult to rigorously analyse, and research has tended to focus on the individual-level, rather than the larger institutions and social networks that produce and disseminate contrarian information. This study presents a new approach by using network science to uncover the institutional and corporate structure of the climate change counter-movement, and machine-learning text analysis to show its influence in the news media and bureaucratic politics. The data include a new social network of all known organizations and individuals promoting contrarian viewpoints, as well as the entirety of all written and verbal texts about climate change from 1993–2013 from every organization, three major news outlets, all US presidents, and every occurrence on the floor of the US Congress. Using network and computational text analysis, I find that the organizational power within the contrarian network, and the magnitude of semantic similarity, are both predicted by ties to elite corporate benefactors.

More attention needs to be given to the intersection of the natural sciences, social sciences, and the private sector, to uncover the structural roots of why, in the face of overwhelming scientific consensus, only 44% of Americans believe that anthropogenic climate change is happening, and only 14% are 'very' worried about its consequences[5]. We understand relatively little about these questions because, with a few exceptions[6–9], most popular and scholarly attempts to explain widespread doubt about climate change have focused on individual-level factors using attitudinal surveys or psychological experiments[10–15]. Although important, this research has focused on outcomes rather than causes—and on individual attributes within the public rather than the institutional actors who produce contrarian information, the social network within which they are embedded, and the flows of resources that underwrite it. Very little research has been able to take this broader approach and explore these essential aspects because it is often difficult for researchers to obtain the necessary data using conventional methods.

Emerging methods in computational social science[16–19] make possible a new approach whereby it is possible to comprehensively examine both the network structure and discursive influence of the climate change counter-movement at a large scale. The data used here include two interrelated parts: the first being the full institutional and social network structure of climate change contrarianism, and the second being its complete collection of written and verbal texts. This comprehensive social network is made up of 4,556 individuals with ties to 164 organizations involved in promulgating contrarian views. The individuals in this bipartite network include interlocking board members, as well as many more informal and overlapping social, political, economic and scientific ties. The organizations include a complex network of think tanks, foundations, public relations firms, trade associations, and *ad hoc* groups. I explain in detail in the Supplementary Methods how I constructed this network, its representativeness, and the variables I collect on each organization.

A central, and empirically unanswered, question concerns the extent to which the private sector influences the production and diffusion of contrarian information. Research has suggested, but not yet empirically tested, that ExxonMobil (EM) and the Koch family foundations (KFFs) may have played a particularly important role as corporate benefactors[7,8]. I therefore obtained Internal Revenue Service data recording whether or not any of the organizations in the contrarian network received funding from these corporate actors between 1993–2013. The KFFs are the philanthropic arm of Koch Industries, and include the Charles G. Koch Charitable Foundation, the Claude R. Lambe Charitable Foundation, and the David H. Koch Charitable Foundation. It is important to note that although many of these organizations receive corporate funding from a wide variety of sources, these two corporate actors supply the most reliable and theoretically important across-time indicators of corporate involvement.

Although the media and politicians often echo contrarian discourse emphasizing 'debate' and 'controversy'[9,20], we know relatively little about the magnitude of such influence and the potential covariates that might explain it. I apply advancements in computational text analysis to measure the external semantic influence of these organizations. To do this I collected the entirety of all written and verbal texts about 'climate change' or 'global warming' from 1993–2013 from every contrarian organization (40,785 documents containing over 39 million words). These texts include the totality of available press releases, published papers, website articles, scholarly research products, policy studies, and conference transcripts (see Supplementary Methods for more information).

To examine which contrarian organizations' ideas were successfully achieving influence in media and politics, I use latent semantic analysis[21] to compare information in contrarian texts to information in all verbal and written texts about climate change between 1993 and 2013 from three major news outlets (14,943 documents), all US presidents (1,930 documents), and every occurrence on the floor of the US Congress (7,786 documents). The media texts come from LexisNexis and include the left-leaning *New York Times*, the right-leaning *Washington Times*, and the centrist *USA Today*. The written and verbal presidential texts come from The American Presidency Project, and the US Congress texts were obtained from the United States Government Printing Office.

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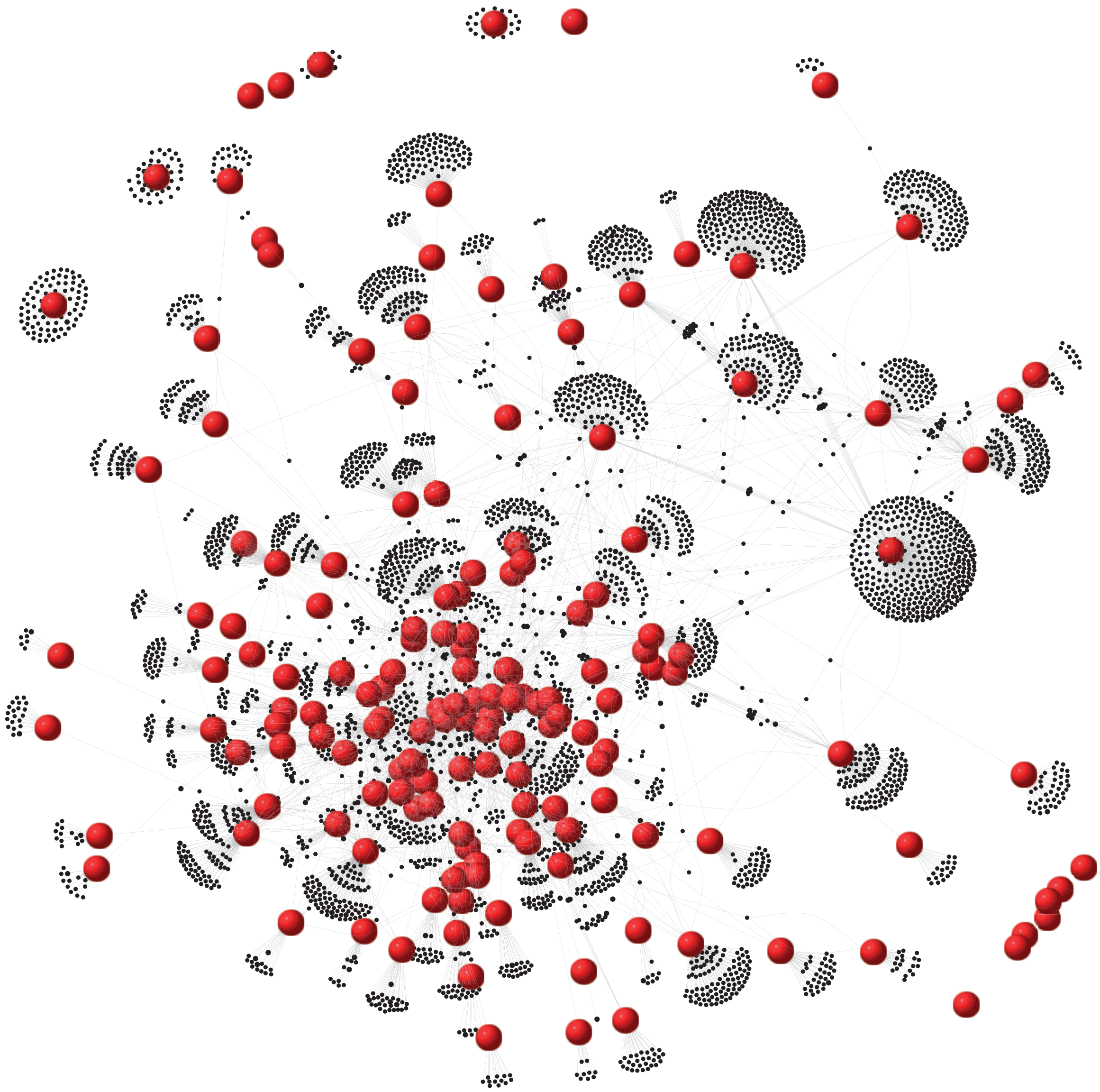

Figure 1 | Bipartite graph of the climate contrarian network. 4,556 individuals (small black nodes) with ties to 164 contrarian organizations (large red nodes).

I use a common form of latent semantic similarity analysis that uses singular value decomposition, and calculates cosine similarity scores between two texts, which is expressed mathematically as:

$$\cos(\mathbf{A},\mathbf{B}) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\,\|\mathbf{B}\|}$$

where **A** is one text from an organization and **B** is one text from news media or politics. The cosine similarity of **A** and **B** ranges from a score of 0 (no similarity) to a score of 1 (perfect similarity). To prepare the texts for similarity analysis, I transformed them into a document term matrix, which includes stripping all whitespace, stemming using the Porter algorithm, converting all words to lower case, and removing all English stop words, sparse terms, numbers, and punctuation. I then use the `lsa` package in `R` to calculate cosine similarity coefficients for every organization by comparing their individual texts to the texts in the same year in news media, presidential, and Congressional data. I computed these for all texts and all years between 1993 and 2013. I then aggregated the mean of the coefficients by year, to assess if contrarian discourse as a whole became more similar over time to the discursive fields they intended to influence. Last, I use multivariate regression to predict organizational differences in these semantic similarity scores.

This approach has several unique theoretical and empirical advantages. First, moving beyond the tendency to focus on individual-level attitudes about climate change, the network approach taken in this study captures the broader social structural arrangements in which contrarian information is actually produced. Second, given the discursive nature of climate change politics, the textual focus on writing and speech is an ideal way to investigate the issue. Collecting the total population of texts in the contrarian network sidesteps biases inherent in small sample sizes that hamper previous studies. Last, these data are naturally occurring phenomenon, and thus avoid many of the pitfalls that nag survey research, psychological experiments, or qualitative interviews.

In Fig. 1 I present a bipartite graph of the global structure of the climate contrarian network, illustrating all ties between individuals (small black nodes) and organizations (large red nodes). Organizations create and exchange information in this network through these individuals, both formally and informally, at climate change conferences, board meetings, media strategy workshops, and political action committee gatherings. Descriptively, I find that

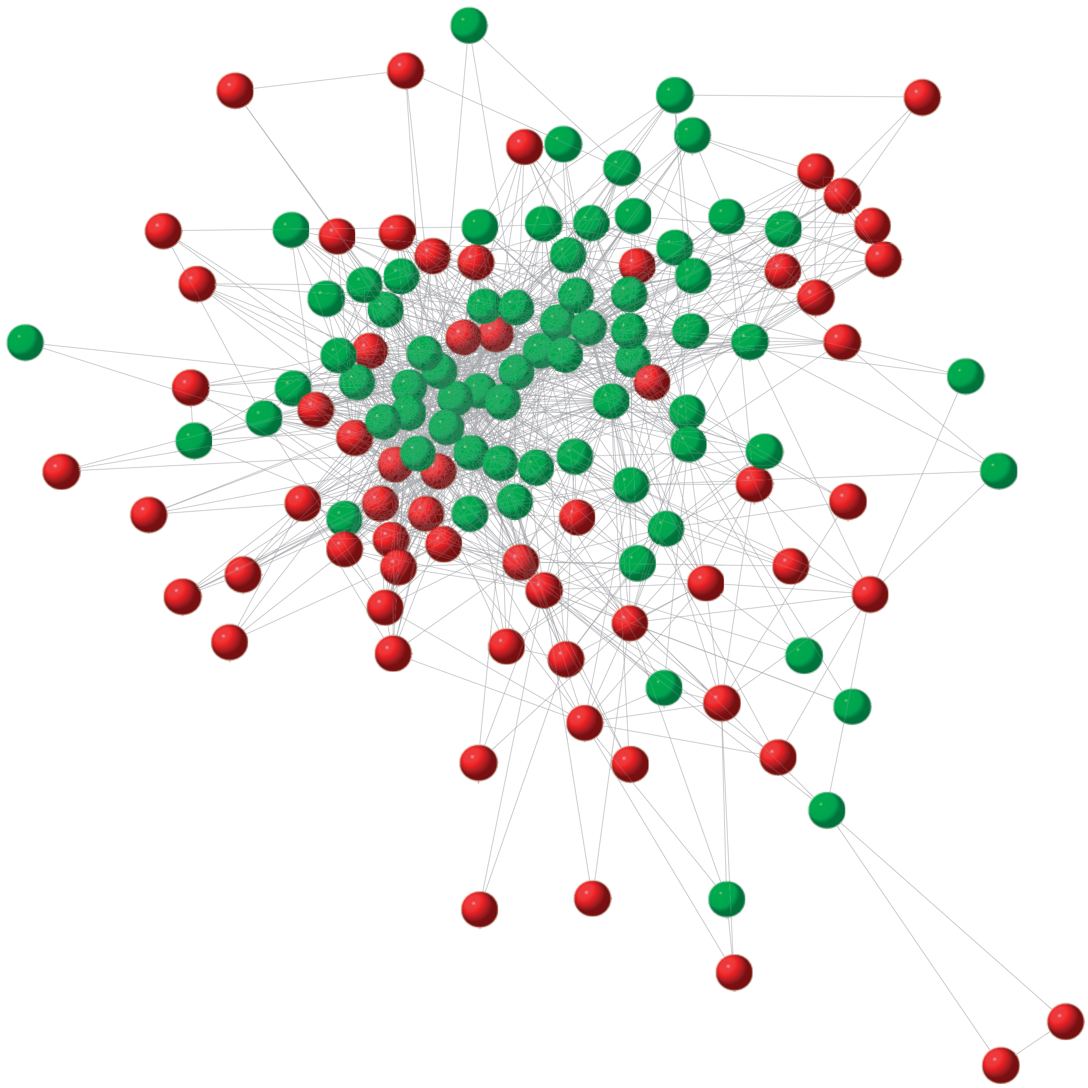

Figure 2 | One-mode organizational structure of the climate contrarian network. Green nodes are organizations who received corporate funding from EM or KFFs, and red nodes indicate no corporate funding from EM or KFFs. Organizations who received such funding have significantly higher centrality scores ($P < 0.01$).

the global structure of this network is such that there are not multiple components, and instead there is a more densely connected region, which is flanked by more loosely connected individuals and organizations.

But to ascertain in more detail the organizational structure of the network, I present a one-mode layout in Fig. 2, where ties between organizations are a function of the ties they share with individuals. For example, in this network a climate change contrarian John Doe might be affiliated with numerous different think tanks, advocacy groups, and foundations—meaning that all of these organizations with ties to John Doe would now share one tie in this graph. Nodes shaded in green indicate organizations that received corporate funding from EM or KFFs, and tend to be located towards the denser middle of the graph. Nodes shaded in red are organizations in the contrarian network that did not receive such funding, and tend to fall on the periphery. To examine within-network differences of organizational power, I calculate betweenness centrality coefficients, which are especially useful in this case for quantifying organizational influence[22]. I found that organizations who received corporate funding from EM or KFFs had significantly higher betweenness centrality scores ($P < 0.01$). Thus, by virtue of their structurally advantageous position within the contrarian network, these organizations have greater influence over flows of resources, communication, and the production of contrarian information.

I did not, however, find that an organization's total assets had a significant impact on its centrality within the network. Similarly, I did not find statistical differences between the total amount of corporate funding an organization received and their network centrality. Thus, what matters most for whether or not an organization is more centrally located within this network has less to do with their financial assets or the amount of donations they receive, but whether or not they had financial ties to corporate benefactors at all, thus signifying entry into an smaller circle of influence.

Next I analysed whether or not contrarian organizations were achieving semantic similarity with news media and politics. At the aggregate level of the entire network corpus, I find a general positive semantic relationship over time with what the news media were writing and what US presidents were saying and writing (Fig. 3). The magnitude of semantic similarity is consistently higher in the news media (between 0.15 and 0.25) than in the two other domains. There is no discernible growth in semantic similarity with US Congress discourse.

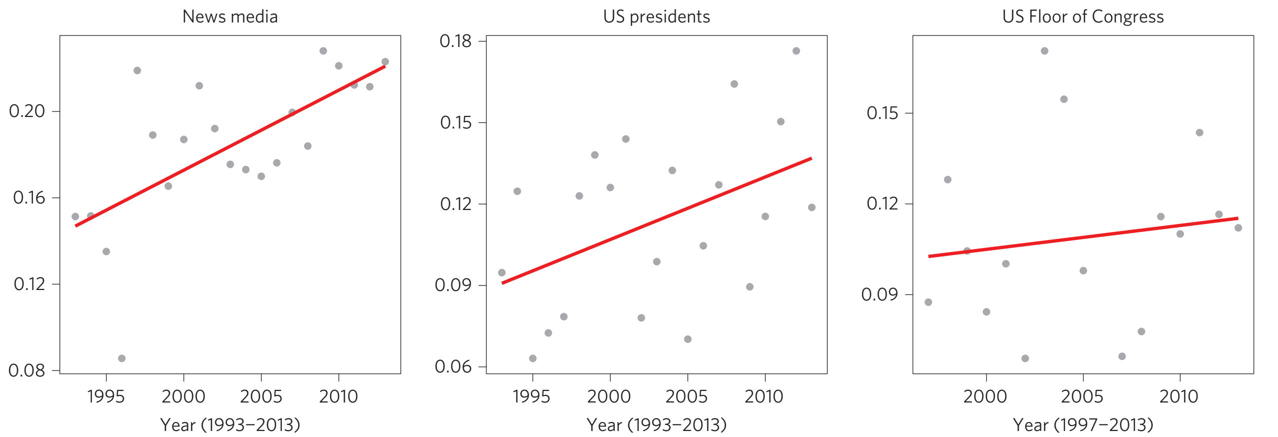

Figure 3 | Growth in semantic similarity with contrarian network discourse. Plotted points are similarity scores, with the linear trendlines indicated in red.

Table 1 | Predicting an organization's semantic similarity with news media discourse.

	Model 1	Model 2	Model 3	Model 4	Model 5
Ties to corporate benefactors	3.74***	3.77***	2.67**	2.94**	3.29***
	(0.81)	(0.84)	(0.91)	(0.92)	(0.96)
Mission focus		1.99	−0.40	−0.55	−0.38
		(1.06)	(1.14)	(1.14)	(1.15)
Network centrality		−0.03	0.01	0.01	−0.10
		(0.19)	(0.19)	(0.19)	(0.21)
Type: Advocacy			8.32***	7.67***	8.04***
			(1.30)	(1.36)	(1.39)
Type: Think tank			4.40***	3.94***	4.28***
			(1.04)	(1.08)	(1.11)
Assets (ln)				−0.25	−0.41*
				(0.15)	(0.19)
Year founded					−0.04
					(0.03)
Year of texts	0.47***	0.45***	0.44***	0.44***	0.45***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Baseline score	−0.07*	−0.06	−0.10**	−0.09*	−0.09**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)

$N=1{,}651$ yearly similarity means, comparing a total of 40,785 texts (nested within individual organizations) to 22,608 news media texts. *** $P<0.001$, ** $P<0.01$, * $P<0.05$.

Although these findings demonstrate a positive relationship in the aggregate, and correspond with prior research[9,20], an important unanswered question concerns which organizations within the network had the highest similarity scores with the news media in particular? Using ordinary least squares regression to predict organizational differences in semantic similarity (Table 1), I found that organizations who had ties to these corporate benefactors (EM or KFFs) predicted significantly higher levels of semantic similarity in the news media ($P < 0.001$). This effect is net of a host of confounding factors including time (the year the text was written), organization assets, network centrality, organization type, the mission focus of an organization, and the year the organization was founded. These important controls are introduced progressively across each of the separate models. I did not find a positive association with regard to total organizational assets, again supporting the conclusion that organizational influence is not simply about sheer financial power, but rather about network power, whereby organizations gain entry into a well connected and powerful core of the network.

These empirical analyses suggest that the successful production and diffusion of contrarian information has a particular network structure and corporate influence. Network power and semantic influence is not spread evenly among organizations in the network, but is concentrated within a smaller group of organizations with ties to particular actors in the private sector. Furthermore, these findings have much broader implications for the privatization of science, the influence of corporate lobbying around scientific issues[23], and by extension, the increasing concentration of corporate wealth in the United States (refs 24,25). These findings also help to explain why climate science rejection is so pronounced in the United States compared to other developed nations. And, given contemporary cuts to state and federal funding of academic research[26,27], a recent AAAS report suggested that science in the twenty-first century will be increasingly shaped by the interests and resources of the private sector[28]. These findings provide evidence of this process, and raise important questions about the privatization of science and the ways in which actors in the private sector impact the networks structure and success of scientific contrarianism. Moving forward, researchers would benefit from adopting this network and computational text approach, to further investigate these complex counter-movement efforts that foster intractable uncertainty, despite the pressing need to mitigate emissions in the face of human and environmental harm.

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Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to J.F.

Competing financial interests

The author declares no competing financial interests.