
2 Abstract

Climate scientists overwhelmingly agree that the Earth is getting warmer and that the rise in average global temperature is predominantly due to human activity. Yet a significant proportion of the American public, as well as a considerable number of legislators in the U.S. Congress, continue to reject the “consensus view.” While the source of the disagreement is varied, one prominent explanation centres on the activities of a coordinated and well-funded countermovement of climate sceptics. This study contributes to the literature on organized climate scepticism by providing the first systematic update of conservative think tank counter-claims in nearly 15 years. Specifically, we 1) compile the largest corpus of climate sceptic claims-making activity to date, collecting over 16,000 documents from 19 organizations over the period 1998 to 2013; 2) introduce a methodology to measure key themes in the corpus which scales to the substantial increase in content generated by conservative think tanks (CTTs) over the past decade; and 3) leverage this new methodology to shed light on the relative prevalence of science- and policy-related discussion among CTTs. We find little support for the claim that “the era of science denial is over”—instead, discussion of climate science has generally increased over the sample period.

3 *Keywords:* climate change, scepticism, text classification, latent Dirichlet
4 allocation

5 1. Introduction

6 Climate scientists overwhelmingly agree that the Earth is getting warmer
7 and that the rise in average global temperature is predominantly due to human
8 activity (IPCC 2014, National Research Council 2010, Oreskes 2004, Doran and
9 Zimmerman 2009, Anderegg et al. 2010, Cook et al. 2013). Yet a sizeable seg-
10 ment of the American public rejects this “consensus view” (Weber and Stern
11 2011) and U.S. climate policy remains in a state of limbo. As of early 2015,
12 one-third of the American public believes that climate change is *not* primarily
13 caused by human activity and only one in ten understands that more than 90% of
14 climate scientists agree on the existence and nature of observed global warming
15 (Leiserowitz et al. 2015). What explains this divergence in views among climate
16 scientists and the American public? What factors promote inaction on compre-
17 hensive climate mitigation policy? These questions have garnered considerable
18 attention in disciplines across the social and behavioural sciences.

19 One prominent explanation investigates the influence of a “well-funded and
20 relatively coordinated ‘denial machine’” on shaping the public’s understanding
21 of climate science (Begley et al. 2007). While a diverse set of actors promote cli-
22 mate scepticism, conservative think tanks (CTTs) play a central role, providing
23 key counter-claims to challenge climate science and obstructing climate policy
24 (McCright and Dunlap 2000). CTTs provide a multitude of services to the cause
25 of climate change scepticism: providing material support and lending credibility
26 to contrarian scientists, sponsoring pseudo-scientific climate change conferences,
27 directly communicating contrarian viewpoints to politicians, and, more gener-
28 ally, disseminating sceptic viewpoints through a range of media to the wider
29 public (Dunlap and McCright 2011). A number of studies also suggest that
30 these organizations are central in obstructing national climate policy (Lahsen
31 2008, Oreskes and Conway 2010) and international climate change mitigation
32 agreements (McCright and Dunlap 2003). The prominence of CTTs in the con-
33 trarian counter-movement has prompted calls for an expansion and improvement
34 of data collection efforts on a range of climate movement and counter-movement
35 activities (Brulle et al. 2012).

36 Despite an active interest in CTTs, few studies have systematically analysed
37 the nature and prevalence of contrarian counter-claims. Aaron McCright and
38 Riley Dunlap’s influential study offers a notable exception, providing a compre-
39 hensive survey of CTT counter-claims from 14 major conservative think tanks
40 over the period 1990-1997. Yet, to our knowledge, there have been no systematic
41 updates to this study over the past 15 years and thus little is known about how
42 contrarian claims have evolved over the last decade. We seek to fill this gap
43 in the literature by 1) compiling the largest corpus of climate sceptic claims-
44 making activity to date, collecting over 16,000 documents from 19 organizations
45 over the period 1998 to 2013; 2) introducing a methodology to measure key
46 themes in the corpus which scales to the exponential increase in content gener-
47 ated by conservative think tanks (CTTs) over the past decade; and 3) leveraging
48 this new methodology to examine the dynamics of policy- and science-related
49 claims over a 16 year period. We argue that understanding CTT counter-claims
50 is of both theoretical and practical significance, as an acceptance of the anthro-
51 pogenic causes of climate change is arguably a necessary condition for progress
52 on reaching a climate agreement and may portend a window for policy action.

53 2. Understanding contrarian counter-claims

54 A number of scholars argue that the entrenchment of climate change scep-
55 ticism in American society is not an “accident.” Rather, the dismal state of
56 public understanding of AGW in the United States is largely the result of an
57 orchestrated attack on climate science and individual climate scientists by a
58 constellation of interests that are determined to obstruct policies aimed at miti-
59 gating global warming (Pooley 2010, Oreskes and Conway 2010, Washington and
60 Cook 2011, Mann 2013). For over twenty years, the American public has been
61 subject to waves of information produced by a “well-coordinated, well-funded

62 campaign by contrarian scientists, free-market think tanks and industry” which
63 has “created a paralyzing fog of doubt around climate change” (Begley et al.
64 2007). Employing tactics (and even participants) from similar disinformation
65 campaigns, such as those against the regulation of tobacco and ozone-harming
66 chlorofluorocarbons (CFCs), the counter-movement aims to block climate policy
67 by “manufacturing doubt” about the credibility of individual scientists, misrep-
68 resenting peer-reviewed scientific findings, and exaggerating scientific uncertain-
69 ties (Union of Concerned Scientists 2007, Oreskes and Conway 2010, Greenpeace
70 2010, Dunlap and McCright 2011).

71 While there are a number key actors in what Begley et al. (2007) refer to
72 as the “denial machine” (see Dunlap and McCright 2011 for an overview), the
73 “engine” of information centres on a number of influential CTTs. CTTs seek
74 to manufacture uncertainty in two important ways. First, sceptics have im-
75 plemented a campaign to re-frame the issue of climate change, shifting the
76 story away from consensus and the urgent need for action toward one of “non-
77 problematicity” (Freudenburg 2000, McCright and Dunlap 2003). Communica-
78 tions research repeatedly emphasizes the sensitivity of public perceptions to how
79 an issue is *framed* within the wider information space (Lakoff 2014, Scheufele
80 and Tewksbury 2007). And given the inherent complexity of climate change,
81 “interpretive storylines” surrounding the issue are ripe for manipulation by par-
82 ties on either side of the debate (Nisbet 2009). Second, relying on their image
83 as the “alternative academia” or “counter-intellegentsia,” CTTs play a lead role
84 in constructing viewpoints to challenge orthodox views on climate science and
85 policy (Beder 2001, Austin 2002, Jacques et al. 2008, Dunlap and Jacques 2013).
86 CTT-affiliated contrarian scientists and commentators have generated and dis-
87 seminated numerous counter-claims against climate science and policy action
88 through various forms of media, including books, op-eds, newsletters, policy
89 studies, speeches and press releases (McCright and Dunlap 2000, Jacques et al.
90 2008, Dunlap and Jacques 2013).

91 Studies interested in measuring the prevalence of contrarian claims focus al-
92 most exclusively on the *level* of contrarian information present in media coverage
93 of global warming. These studies have yielded important insights into the preva-
94 lence of skepticism within newspapers (e.g., Boykoff and Boykoff 2004, Painter
95 and Ashe 2012, Schmidt et al. 2013), opinion pieces in print media (Hoffman
96 2011, Elsasser and Dunlap 2013, Young 2013), television (Boykoff 2008, Hart
97 2008, Feldman et al. 2012), and “new media” (O'Neill and Boykoff 2011, Hol-
98 liman 2011, Knight and Greenberg 2011, Sharman 2014, Elgesem et al. 2015).
99 However, few studies systematically analyse the *content* of contrarian claims
100 and even fewer focus specifically on CTTs. To date, McCright and Dunlap
101 (2000) offers the most comprehensive survey of CTT counter-claims on climate
102 change. The authors content analyse a sample of 224 documents related to
103 global warming from 14 major conservative think tanks over the period 1990-
104 1997, with the vast majority of this literature being produced during 1996 and
105 1997. Overall, the analysis suggests that climate scepticism during this period
106 centred on three major counter-claims: 1) the evidentiary basis of global warm-

107 ing is weak or wrong, 2) global warming would be beneficial if it was to occur,
108 and 3) global warming policies would do more harm than good (see [McCright
109 and Dunlap 2000](#) pg. 510, Table 3). For the 1990-1997 period, the study finds
110 that 71% of the documents contained criticisms of the scientific evidence for
111 global warming (Counter-claim 1), only 13.4% discussed the benefits of global
112 warming (Counter-claim 2), and 62.1% provided a discussion on the downsides
113 of climate policy action (Counter-claim 3).

114 McCright and Dunlap’s study provides a unique look at sceptical counter-
115 claims in the mid-to-late 1990s, yet much less is known about how these claims
116 have evolved. Several studies provide a more recent look at the key features of
117 the contrarian discourse more generally. [Elsasser and Dunlap \(2013\)](#) employed
118 John Cook’s list of sceptical arguments (www.skepticalscience.com) to classify
119 203 op-eds over the period 2007-2010. The authors find that personal attacks
120 on Al Gore and scepticism of the IPCC were common throughout the corpus,
121 while “it’s not happening” arguments dominated the discussion, showing up in
122 almost two thirds of the articles. [Sharman \(2014\)](#) examines the climate skeptic
123 blogosphere from March to April of 2012, classifying 171 blog posts as either
124 science- or policy-oriented. The author finds that blogs which are “central” in the
125 blogosphere network tended to focus on discussions of science, while peripheral
126 blogs tended to emphasise policy. Lastly, and more in line with the current
127 study, in a content analysis of documents from the Heartland Institute over the
128 period September-December 2013 ($n = 102$), [Cann \(2015\)](#) finds a considerable
129 drop in discussions of policy when compared to the findings of [McCright and
130 Dunlap \(2000\)](#). As the author acknowledges, however, it is difficult to determine
131 whether this indicates a general move away from policy-oriented claims or is
132 simply a sampling issue associated with focusing on a single organisation for a
133 two month period. More generally, this limitation applies equally to the analysis
134 of op-eds and blogs as well: the existing evidence provides segmented glimpses of
135 the evolution of contrarian claims over the past decade and a half. The remainder
136 of this study seeks to overcome this limitation by providing a comprehensive look
137 at CTT claim-making activity.

138 **3. Measuring contrarian claims**

139 *3.1. The corpus*

140 To systematically gauge claims-making activity, we retrieved information re-
141 lated to climate change from the websites of 19 well-known North American
142 conservative think tanks and organizations (see online appendix for details).
143 Our choice of organizations, to a large extent, mirrors that of [McCright and
144 Dunlap \(2000\)](#) and the most heavily funded organizations which are identified
145 in [Brulle \(2014\)](#). For each organization, we visited all pages including the terms
146 “climate change” or “global warming” and extracted relevant text and key meta
147 data. There were also instances where pages included links to documents in PDF
148 format, which were typically relatively long policy reports. These PDFs were
149 automatically retrieved, passed through optical character recognition (OCR)

Organization Name	Total Words (thous.)	Total Docs.	Document Type				
			A	B	C	D	E
American Enterprise Institute (AEI)	1,872.53	745	596	61	48	15	25
Cato Institute	772.68	768	712	41	8	6	1
Center for the Study of Carbon Dioxide and Global Change (CO2Science)	2,387.27	4,592	713	0	0	1	3,878
Competitive Enterprise Institute (CEI)	1,743.02	1,461	941	55	0	465	0
Committee for a Constructive Tomorrow (CFACT)	738.52	894	882	12	0	0	0
Citizens for a Sound Economy (CSE)	88.2	111	105	6	0	0	0
Fraser Institute	78.39	81	62	19	0	0	0
Foundation for Research on Economics and the Environment (Free-Eco)	76.64	105	105	0	0	0	0
Heartland Institute	9,900.54	2,930	1,383	1,537	10	0	0
Heritage Foundation	1,825.78	1,652	1,198	431	23	0	0
Hoover Institution	51.06	37	3	32	2	0	0
Hudson Institute	124.61	83	81	2	0	0	0
Manhattan Institute	315.59	199	183	13	3	0	0
George C. Marshall Institute	209.75	101	69	21	11	0	0
National Center for Policy Analysis (NCPA)	469.78	451	376	75	0	0	0
National Center for Public Policy Research (NCPPI)	393.54	639	378	90	0	171	0
Pacific Research Institute	384.68	435	402	7	0	26	0
Reason Foundation	397.12	192	179	13	0	0	0
Science and Public Policy Institute (SPPI)	3,064.88	552	0	552	0	0	0
Total	24,894.58	16,028	8,368	2,967	105	684	3,904

Table 1: *Climate sceptic organizations.* The table displays the total count of words (thousands), the number, and type of documents from 19 well-known conservative think-tanks over the period January 1998 – August 2013. Documents have been classified as follows: (A) op-eds, articles and blogs; (B) policy/science reports and analyses; (C) speech/interview transcripts; (D) press releases/open letters; (E) scientific reviews.

150 software to extract the text, and appended to the list of text retrieved from the
151 HTML code. Audiovisual materials were a minority of the overall set of retrieved
152 pages and were excluded in the current analysis. This process produced more
153 than 16,000 documents over the period from 1998 to 2013.

154 Table 1 provides an overview of the organizations included in the sample. The
155 first two columns display the total number of words and documents published
156 online by each organization over the period of study. To provide a general sense of
157 the types of output, the next five columns provide a tabulation of the documents
158 by type, following the classification scheme used in (McCright and Dunlap 2000,
159 p. 508). Relying heavily on meta-data provided within the URL or the document
160 itself, we categorize the documents by five general types: (A) op-eds, articles and
161 blogs, (B) policy/science reports and analyses, (C) speech/interview transcripts,
162 (D) press releases/open letters, and (E) scientific reviews. More information on
163 the document type coding procedure is available in the online appendix.

164 The table provides a number of insights into the claims-making behaviour

165 of the most important CTTs. First, these organisations have increased their
166 production and dissemination of literature exponentially, from roughly 203 doc-
167 uments over the period 1990-1997 (McCrigh and Dunlap 2000) to 16,028 docu-
168 ments for the years 1998-2013. Second, the distribution of the document classi-
169 fications suggests that the communication strategy of these organizations varies.
170 Several organisations focus on producing shorter, op-ed style documents (e.g,
171 NCPA), while others focus on producing lengthier policy or science-related re-
172 ports (e.g, George C. Marshall Institute). Third, as expected based on past
173 research, the Heartland Institute is a central actor among CTTs, producing or
174 disseminating a significant portion of the documents in the corpus and focusing
175 on a mix of short articles and longer policy reports. We take a closer look at
176 the claims-making trends of Heartland in Section 6.

177 3.2. Methods: probabilistic topic modelling

178 The time and effort associated with reading over 16,000 documents renders
179 traditional content analytic approaches inadequate and/or infeasible and thus
180 the next step is to find a suitable computational model to help make sense of
181 the data. We approach this step using an *unsupervised* approach, exploring
182 the presence of meaningful clusters of terms that appear across documents in
183 the collected corpus. While there is no shortage of clustering algorithms in the
184 literature (Grimmer and King 2011), we utilize the latent Dirichlet allocation
185 (LDA) model originally proposed in Blei et al. (2003). LDA provides a statistical
186 framework for understanding the latent topics or themes running through a
187 corpus by explicitly modelling the random process responsible for producing
188 a document. The LDA model assumes that each document is made up of a
189 mixture of topics, as well as a mixture of words associated with each topic. For
190 instance, the document you are reading at this moment includes a mixture of
191 themes such as “climate scepticism” and “text analysis,” and these themes tend
192 to use different language—the topic “climate scepticism” is likely associated with
193 the word “denial,” whereas the topic “text analysis” is associated with the word
194 “random.” Moreover, this process is probabilistic in the sense that we could have
195 used the term “stochastic” instead of “random” in the previous sentence.

196 This basic generative story provides the basis for a simple hierarchical Bayesian
197 model based on the following assumptions: 1) each word in a text is exchange-
198 able, each text in a corpus is a combination of a specific number of topics (T_k),
199 and each specific topic is represented as a distribution of words (w) over a fixed
200 vocabulary (Blei et al. 2003, Griffiths and Steyvers 2004). The generative struc-
201 ture that produces each document in a corpus is represented as random mixtures
202 of latent topics and their associated distributions of words. Specifically, the LDA
203 assumes that documents are generated from the following probabilistic process:

- 204 1. Each of the k topics are drawn from a topic distribution by

$$205 \theta \sim \text{Dirichlet}(\alpha)$$

- 206 2. The term distribution β for each topic is represented by

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$$\beta \sim \text{Dirichlet}(\eta)$$

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3. For each of the N words w_n :

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Randomly sample a topic $z_n \sim \text{Multinomial}(\theta)$.

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Choose a word w_n from $p(w_n|z_n, \beta)$.

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Although this model provides an overly simplified representation of the true data generating process for text, it has been shown to be effective in applied situations and employed in a diverse range of fields, from population biology to information retrieval (see [Blei 2012](#) for an overview).

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3.2.1. How many topics?

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LDA requires one to specify the number of topics *a priori*. This presents an obvious challenge when studying contrarian counter-claims, as past research suggest anywhere from 9 claims ([McCright and Dunlap 2000](#)) to 176 “debunked climate myths” (www.skepticalscience.com). While a range of methods have been introduced in the literature to estimate the “natural” number of topics (see [Wallach et al. 2009b](#) for an overview), there remains considerable debate on the utility of data-driven approaches for generating interpretable topics ([Chang et al. 2009](#)). Moreover, when applying probabilistic topic models to understand social phenomena, the “natural” number of topics is conditional on the particular research question of interest. If answering your question requires a high degree of detail, then using a larger number of topics is advisable; otherwise, little substantively meaningful information is lost by assuming a smaller number of topics ([Quinn et al. 2010](#), [Roberts et al. 2014](#)).

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With little theoretical guidance on the appropriate number of topics, we employ a balanced approach between data-driven methods and a qualitative assessment of the interpretability of the latent space. First, we rely on the topic selection criteria proposed in [Arun et al. \(2010\)](#), which has proven an effective heuristic for determining a reasonable topic number in both real and synthetic datasets (see the online appendix for technical details). Using the Arun et al. procedure as a starting point, we then systematically adjusted the assumed topic number (k) around the “optimal” data-driven result and manually assessed the quality of the topic solutions. While the details of this analysis are available in the online appendix, we find that $k = 53$ offers a suitable balance between having a manageable number of topics, enough detail to assess core substantive themes in climate contrarianism, displaying a reasonable level of “fit” using data-driven methods, and demonstrating stability across a range of solutions.

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4. Results

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4.1. Model estimation and topic interpretation

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We estimate the model using the sparse Gibbs sampler described in [Yao et al. \(2009\)](#) and the hyperparameter optimization routine utilized in [Wallach et al. \(2009a\)](#). Consistent with the findings in [Wallach et al. \(2009a\)](#), we found that optimizing α , while fixing β , provided the easiest results to interpret and

248 thus employ this specification. Moreover, given that mixture models such as the
249 LDA are known to produce multimodal likelihood surfaces, we used a number
250 of different random starting values. We found a good deal of stability in the
251 estimated topic distributions across runs, improving our confidence that the
252 model converged on a global optimum.

253 After removing 6 “junk” topics (AlSumait et al. 2009),¹ our final list in-
254 cludes 47 substantively meaningful topics representing a range of issues related
255 to global warming. Table 2 provides a complete list of the estimated topics of
256 the sceptical discourse. To ease interpretation, we produce a descriptive label for
257 each topic by reading the 10 most probable documents and noting the key theme
258 consistent within each sub-sample. The descriptive labels not only provide use-
259 ful information to facilitate topic interpretation, but also offer a first look at one
260 aspect *semantic validity*: the extent to which each topic is coherent in terms of
261 its meaning (Quinn et al. 2010). We also include a set of keywords for each topic
262 based on the word’s “frequency-exclusivity” (FREX), as described in Roberts
263 et al. (2014). FREX offers a balance between the probability (or “frequency”) of
264 a word being associated with a particular topic and the extent to which a word
265 is unique to a topic (i.e., “exclusivity”).

266 Looking at the full list of topics shown in Table 2, the results demonstrate a
267 good level of face validity and are generally consistent with the themes discussed
268 in McCright and Dunlap (2000). These topics touch on a wide range of themes
269 such as scientific integrity and uncertainty, climate change impacts, energy, en-
270 vironmental policy, society, as well as domestic and international politics. And,
271 as expected, the corpus is rife with claims surrounding the uncertainty of cli-
272 mate scientific studies. The notion that human activity, specifically the emission
273 of greenhouse gases into the atmosphere, is leading to a rise in global tempera-
274 tures (topic 1) has been characterized as suffering from a “real-world disconnect”
275 (Heartland Institute, Nov. 11, 2011) and any discussion to the contrary amounts
276 to “alarmism” (Heartland Institute, May 17, 2013). Further, the general agree-
277 ment of scientists on this relationship is repeatedly refuted within the corpus
278 (topic 4) as there is “no consensus on climate change” (NCPR, March 22, 2004).
279 Appeals to long-term natural cycles in temperature (topic 5), as purportedly
280 demonstrated by the Roman and Medieval Warm Periods, are common support
281 for arguments against anthropogenic global warming. This topic is of particular
282 interest as it was not detected in McCright and Dunlap (2000) and has become
283 a common claim among climate sceptics. Studies that support anthropogenic
284 global warming are also deemed to be “fabricated” and have led to a “childish
285 panic.” Typical examples of these arguments include:

¹AlSumait et al. (2009) note that not all topics in an estimated topic model are of equal importance and it is not uncommon to have a set of “junk” topics that pick up common co-occurrences of words with little or no substantive meaning.

Id	S/P	Topic Name	Id	S/P	Topic Name
42	S	Acidification calcif reef bleach coral phytoplankton	20	P	Corporations & env. borelli sharehold greenpeac donor philanthropi
16	S	Alarmism gore morano romm inconveni depot	43	P	Disaster costs insur pension mortgag florida premium
11	S	Climate models simul gcm model cmip coupl	25	P	Economic impact of climate policy baselin discount sector eia mit
1	S	Climate sensitivity to CO2 warm degre cool dioxid warmer	29	P	Emissions reduction carbon scheme credit trade dioxid
46	S	Endangered species butterfli stirl extinct bear polar	10	P	Environmentalism lomborg holdren ehrlich evangel simon
34	S	Forest impacts npp ndvi shrub peatland finzi	38	P	EPA caa epa endanger naaq anpr
19	S	Human health ddt precautionari malaria diseas cancer	2	P	Fossil fuel production shale barrel oil drill pipelin
27	S	IPCC integrity chapter ipcc tsd wg summari	15	P	Govt. agencies fy sec gao omb provis
5	S	Long-term climate trends holocen millenni quaternari mediev palaeo	9	P	Govt. intervention approach intervent principl geoengin outcom
26	S	Monckton monckton graph ppmv brenchley humankind	24	P	Green jobs job stimulu taxpay subsidi green
4	S	No scientific consensus consensu denier oresk agw scientif	44	P	Int'l climate agreements kyoto protocol treati ratifi ratif
30	S	Plant impacts seedl leaf mycorrhiz cultivar elev	17	P	Int'l relations militari nato missil afghanistan iran
45	S	Pollution mercuri ozon toxic asthma particul	31	P	Int'l trade & develop india china chines wto asia
14	S	Scientific misconduct cru mcintyr mann hockey email	39	P	Law court judici lawsuit constitut suprem
3	S	Sea level rise antarct greenland glacier melt antarctica	23	P	Nuclear power hydrogen reactor nuclear technolog cell
12	S	Solar forcing & cloud models cosmic cloud radiat ray aerosol	6	P	Public opinion gallup abc pew cnn cb
40	S	State climate reports viru cessat Nile wigley inch	36	P	Public transportation rail ridership travel passeng vmt
28	S	Storms cyclon storm hurrican tc frequenc	8	P	Renewable energy rp turbin renew wind megawatt
13	S	Temperature station data station giss ushcn fig thermomet	22	P	Reuse & recycle bag mtbe bulb cfl reus
18	P	Agri. Industry corn ethanol biofuel farmer sugar	41	P	State climate policy ghg jersey greenhous wefa rggi
47	P	Auto. fuel standards cafe nhtsa mpg vehicl car	32	P	Tax & spend tax dividend incom fiscal medicaid
35	P	Cap & trade markey waxman lieberman warner cap	21	P	Urban econ. california ab metropolitan schwarzenegg californian
37	P	Climate adaptation goklani adapt stern mitig resili	7	P	US politics republican sen mccain democrat vote
33	P	Conservation timber eagl fisheri perc graze			

Table 2: *A full list of the estimated topics.* The table provides each topic’s unique ID, descriptive label (in bold), and top 5 stemmed keywords based on the FREX score (Roberts et al. 2014). Further, based on the findings from the topic similarity analysis in Section 5.1, we code whether each topic is related to climate science (S) or climate politics & policy (P).

286 Global temperatures have been flat for approximately 15 years now, even though
287 atmospheric carbon dioxide levels rose more than 40 ppm (or more than 10
288 percent) during that time. Rather than being a harbinger of doom and gloom,
289 the approaching 400 ppm carbon dioxide threshold presents still more evidence
290 that humans are not creating a global warming crisis (Heartland Institute, May
291 17, 2013).

292 The existence of the [Medieval Warm Period] had been recognized in the sci-
293 entific literature for decades. But now it was a major embarrassment to those
294 maintaining that the 20th century warming was truly anomalous. It had to be
295 “gotten rid of” (NCPA, Dec. 6, 2006).

296 Many documents also suggest alternate climate forcing inputs such as the sun
297 or cosmic rays (topic 12) as more plausible explanatory factors for climate fluc-
298 tuations than greenhouse gas emissions. The validity and reliability of empirical
299 data used in climate change studies (topic 13) to demonstrate global warming
300 impacts are cast into doubt. Further, the underlying assumptions of climate
301 change models (topic 11) that are referenced in the IPCC assessments are of
302 “dubious merit” (Fraser, July 7, 2004).

303 The results of the LDA model also demonstrate the breadth of topics dis-
304 cussed in documents referencing climate change with important issue linkages
305 across both the domestic and international political economy. Much critical
306 discussion surrounds international mitigation policies (topic 44) as threats to
307 national sovereignty and expected detrimental impacts to the economy (topic
308 25). Renewable energy technologies such as solar and wind (topic 8) as well
309 as biofuels (topic 18) are almost always presented as inadequate solutions on
310 their own. Fossil fuel production (topic 2), on the other hand, is discussed in
311 positive terms, typically in relation to energy independence and technological
312 innovation. For instance, an expansion of oil drilling into the Arctic National
313 Wildlife Refuge (ANWAR) has been framed as an “important part of a pro-
314 consumer energy policy” that will make energy “plentiful and affordable” (CEI,
315 March 14, 2005). The harmful impacts of regulation in the energy sector, such
316 as GHG emissions reductions (topic 29), automobile fuel standards (topic 47)
317 and cap-and-trade policy (topic 35), are also discussed negatively. For instance:

318 Whether the American economy is booming or heading off a fiscal cliff, the right
319 time for a carbon tax is never (Heritage Foundation, January 8, 2013).

320 [A] carbon tax would raise family energy prices by more than \$500 per year, jack
321 up gasoline prices 50 cents per gallon, reduce family income by nearly \$2,000,
322 and cost 1 million jobs by 2016 alone. Since developing nations like China and
323 India will continue increasing their CO2 no matter what the U.S. does, a carbon
324 tax is a bad solution to a still-unproven problem (CFACT, February 15, 2013).

325 Overall, the Lieberman-Warner bill promises substantial hardship for the econ-
326 omy overall, for jobs, and for energy costs. Given current economic concerns and
327 energy prices, this is the last thing the American people need. At the same time,
328 the environmental benefits would likely be small to nonexistent. The Lieberman-
329 Warner bill fails any reasonable cost-benefit test (Heritage Foundation, May 30,
330 2008).

331 Further, the integrity of climate scientists is also frequently questioned, es-
332 pecially in relation to the peer-review process of the IPCC (topic 27) and other
333 perceived violations of scientific integrity (topic 14) such as the so-called “cli-
334 mategate” email controversy of late 2009 which supposedly has dealt a “death
335 blow” to the global warming “fraud” (Heartland Institute, Nov. 21, 2009). Nu-
336 merous documents take aim at the credibility of climate scientists; the following
337 excerpt serving as a typical example.

338 The purloined letters show a climate-science community in full tribal mode, con-
339 spiring to suppress contrary findings in the peer-reviewed literature; excluding
340 contrary peer-reviewed publications from IPCC reports; concealing the shoddy
341 nature of climate data; colluding to hide data and destroy correspondence; and
342 using mathematical tricks to produce ever more alarming-looking charts (Amer-
343 ican Enterprise Institute, Nov. 25, 2009).

344 These conspiracy-based themes are related to a broader trend within the corpus
345 of equating scientific findings on climate change with “alarmism” (topic 16),
346 where individual scientists and activists are presented as fomenting a state of
347 panic based on inconclusive or even fabricated evidence. Al Gore, for example,
348 has been accused of using “distorted evidence” to further a “scare-them-green
349 agenda” (CEI, March 16, 2007). More generally, “global warming alarmists”,
350 such as climate scientist Michael Mann, are accused of being in the business
351 of “spreading myths and misinformation to further their agenda” (Heartland
352 Institute, June 29, 2012). For example:

353 Mann’s claims that human’s [sic] have caused tremendous warming over the last
354 100 years and that the 1990s were the warmest decade are untenable [...] Looking
355 at the data, the global warming scare appears to be merely ‘Mann made’ junk
356 science (NCPA, July 12, 2004).

357 5. Assessing model quality: reliability and validity

358 It is crucial when coding themes to establish sufficient levels of reliability and
359 validity. Traditionally, difficulties associated with determining reliability have
360 plagued content analytic studies, as a single coder’s judgements may be highly
361 subjective. While subsequent studies have shown that relying on multiple coders
362 and establishing sufficient inter-coder reliability may yield consistent measure-
363 ment in repeated trials, few content analytic studies in the literature on climate
364 scepticism report any reliability estimates. This is understandable given that
365 reproducing measures based on traditional methods is a costly endeavour. On
366 the other hand, this is one area where automated approaches excel—improved
367 reliability is often considered a key benefit of employing a computer-assisted
368 approach (Laver and Garry 2000, Laver et al. 2003). Once the text is collected
369 and the model is programmed, the measuring procedure should yield *exactly* the
370 same results in repeated trials.

371 Although the benefits of employing automated methods for reliability are
372 clear, the same cannot be said for validity and thus the onus is on the researcher

373 to establish the soundness of their results when using computer-assisted ap-
374 proaches. [Grimmer and Stewart \(2013\)](#), in a review of the text analysis litera-
375 ture in political science, argue emphatically for the need to “[v]alidate, validate,
376 validate,” stating “that what should be avoided, then, is the blind use of any
377 method without a validation step” (pg. 5). This section devotes considerable
378 attention to this “validation step,” using multiple methods to examine diverse
379 conceptions of validity. Specifically, we 1) provide further evidence of the *se-*
380 *mantic* validity of our findings, 2) assess *predictive* validity via external events,
381 and 3) examine *concurrent* validity by comparing the model output to a human
382 gold standard.

383 5.1. *Semantic validity and topic similarity*

384 While the descriptive labels described in Section 4.1 offer initial support for
385 semantic validity, an additional means of examining this criterion assesses the
386 extent to which topics relate to one another in substantively meaningful ways
387 ([Quinn et al. 2010](#)). Note that a “topic” in the LDA model is represented by
388 a probability distribution—i.e., the distribution of words given the topic—and
389 thus the notion of “topic similarity” centres on the distance between two proba-
390 bility distributions. While there are a number of metrics available for examining
391 the distance between probability distributions, a common approach is to rely on
392 the well-known Kullback-Leibler (KL) divergence or the related Jensen-Shannon
393 divergence (JSD). We examine similarity (or dissimilarity) using the square root
394 of JSD (sometimes referred to as Jensen-Shannon “distance”), which rescales
395 the JSD into a proper metric ([Endres and Schindelin 2003](#), [Osterreicher and
396 Vajda 2003](#)). Intuitively, when two topic distributions are more similar, they
397 will share a smaller JS distance and vice versa. Figure 1 presents this infor-
398 mation graphically by mapping the pairwise distances onto a two dimensional
399 space using classic multi-dimensional scaling ([Gower 1966](#)). Topics that address
400 similar themes—and thus rely on similar words with high probability—should
401 be relatively close to one another in Figure 1, while dissimilar themes should be
402 further way.

403 The results of this analysis are striking. First, we observe a set of meaningful
404 clusters, with topics related to politics, policy and regulation, energy, climate
405 science, and scientific integrity located in distinct areas of the figure. Moreover,
406 when looking *within* the principal areas, the topics also cluster as expected. For
407 instance, considering the “Policy & Regulation” theme, topics associated with
408 government regulation (15 and 38) inhabit the lower portion of the cluster which
409 is closer to the “Domestic & Int’l Politics” cluster, while the upper area deals
410 with themes more associated with government planning (22, 32, and 33). It is
411 not a surprise that *Tax & Spend* (32), for example, is closer to the “Energy”
412 cluster, as most discussions related to energy policy involve burdensome taxes on
413 fossil fuel consumption. Second, the distance between the four main issue areas
414 fits with intuition. As expected, “Energy”, “Policy & Regulation” and “Do-
415 mestic & Int’l Politics” are quite far away from the “Science” cluster. Perhaps
416 most interesting, however, are the findings associated with scientific integrity.

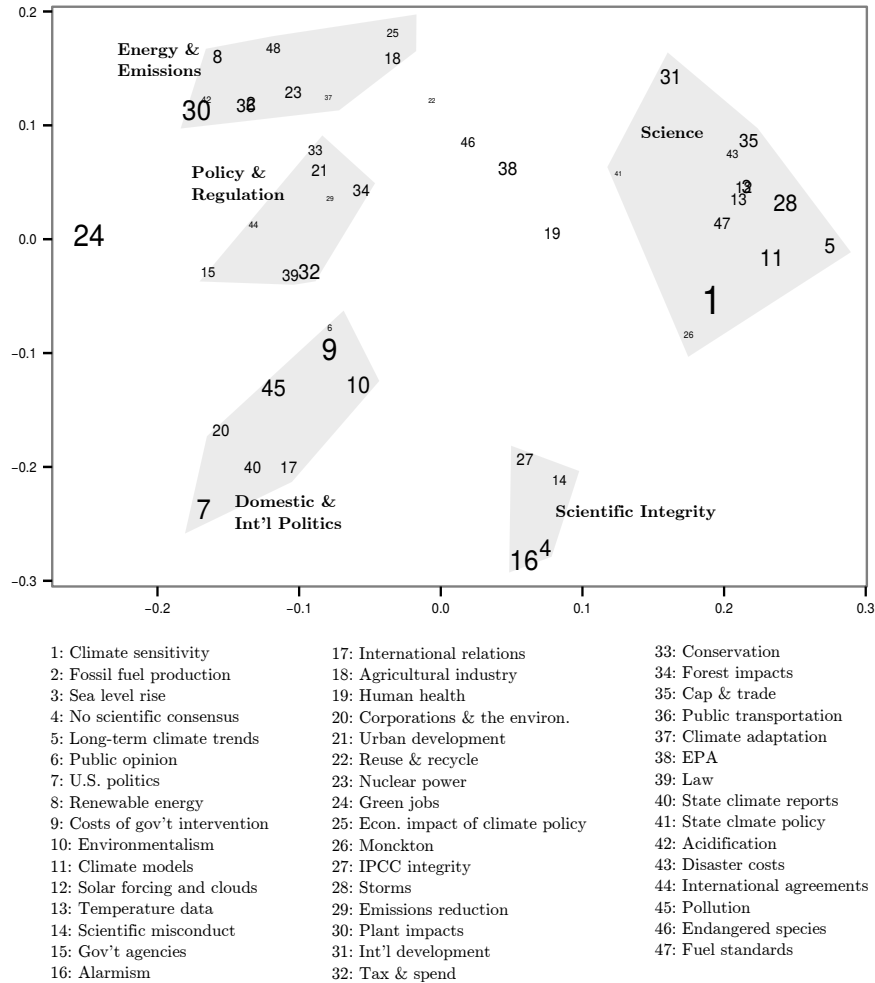


Figure 1: *Topic similarities.* The figure presents Jensen-Shannon distances projected onto a 2D space via multi-dimensional scaling. The size of plotted label corresponds to the number of times the topic was sampled in the corpus and thus gives a rough indication of topic importance. Topics using similar words will be closer together in the figure and vice versa. To ease visualization, we plot the convex hull for each cluster in grey.

417 Not only do topics dealing with scientific misconduct—both regarding scientists
 418 themselves, the scientific consensus on AGW, and the IPCC in general—form
 419 their own distinct cluster, the language used seems to have more in common with
 420 politics than science; that is, scientists are presumed to wield “junk science” to

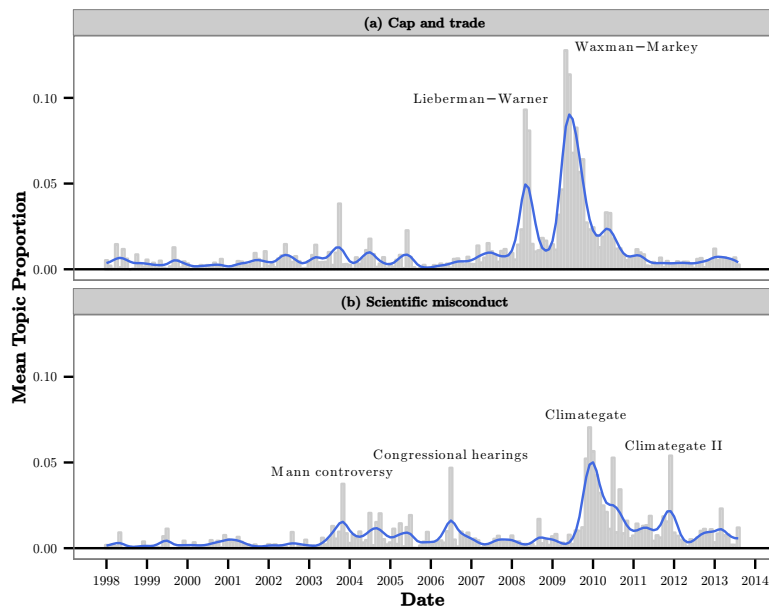


Figure 2: *Predictive validity based on external events.* The graphs illustrate the average monthly topic proportions of four topics over the period January 1998 – August 2013. A local polynomial trend line is included to assist interpretation.

421 achieve political aims. Lastly, a number of topics are at the crossroads between
 422 important issue areas. For example, *Climate adaptation* (37) is located at the
 423 nexus between science and policy, which is not surprising given that adapta-
 424 tion focuses on using climate science to understand the adverse impact of global
 425 warming and implementing policies to prevent or mitigate potential damage.
 426 What is surprising is that a simple model based on word co-occurrences is able
 427 to detect this nuance. Taken together, we find that the 47 topics cluster onto a
 428 smaller set of theoretically meaningful and valid higher-order themes.

429 5.2. Predictive validity and topic dynamics

430 To further assess the quality of our classifications, this section examines
 431 the *predictive validity* of the estimated model—i.e., the extent to which our
 432 topics are predicted by external events (Quinn et al. 2010). However, prior to
 433 examining the relationship between key contrarian claims and external events,
 434 it is necessary to decide on a suitable measure of topic prevalence over time. We
 435 turn to this challenge in the next section.

436 5.2.1. *Measuring topic prevalence over time*

437 There is little agreement in the literature regarding the “best” way to com-
438 bine underlying topic probabilities to produce aggregate level measures and, as
439 with issues of measurement more generally, the appropriateness of an item is
440 often contingent on the research question under consideration. While assumed
441 measures may vary in a number of different ways, the key question for under-
442 standing contrarian claims over time is whether one captures *absolute* or *relative*
443 topic prevalence. An absolute measure allows the “information pie” to grow over
444 time, while its relative counterpart holds the pie constant, instead focusing on
445 the competition among counter-claims within a specified time frame. We rely on
446 two measures—one absolute and the other relative—to formulate the descriptive
447 analysis below. The first (absolute) measure simply sums the topic proportions
448 for a particular topic in a given period of time (e.g. the proportions for the
449 “Alarmism” topic during December 2008), while the second (relative) focuses
450 on the mean topic proportion within a specified time frame. One implicit as-
451 sumption is that each measure gives equal weight to the topic proportions across
452 documents and thus ignores document length. Given the extremely skewed dis-
453 tribution of word lengths in our corpus, however, the proposed measures offer
454 a more stable estimate of topic prevalence and avoid the equally problematic
455 assumption that document importance scales linearly with word length. More-
456 over, estimates using a suitable nonlinear transformation of the word counts
457 (e.g., taking the log) offer virtually identical results in both cases and thus our
458 measurement choice appears robust.

459 5.2.2. *Assessing predictive validity via external events*

460 Figure 2 provides the mean topic proportion for two topics, *Cap & trade* (35)
461 and *Scientific misconduct* (14), for each month over the period from January
462 1998 to August 2013. First, turning to cap-and-trade (see the top panel of
463 Figure 2(a)) two months—May 2008 and August 2009—clearly stand out. The
464 first large peak coincides with the Senate vote on the Lieberman-Warner bill
465 (America’s Climate Security Act of 2007). Significant opposition to the bill found
466 within the corpus largely argues that the legislation would do massive damage
467 to the national economy while offering modest to no environmental benefits.
468 The second significant spike occurs in August 2009, just after House approval of
469 the Waxman-Markey bill (American Clean Energy and Security Act of 2009).
470 Similar types of arguments that were used against the Lieberman-Warner bill
471 also surfaced during the Waxman-Markey period. Following the defeat of the
472 Waxman-Markey bill, we see a sharp decline in discussions surrounding emissions
473 reduction legislation. However, a resurgence of the topic occurs in 2013, with
474 much attention being placed on the dangers of a carbon tax for the economy.

475 Figure 2(b) displays the share of words dealing with a scientific misconduct
476 theme. A sustained period of interest seems to cover the 2003-2005 period,
477 with the release of papers from climate sceptics such as Stephen McIntyre, Ross
478 McKittrick, and Hans von Storch, which criticize Michael Mann’s methodology.
479 The next substantial increase in the topic proportion is observed in July 2006,

480 when Congressional hearings were held on the validity of Mann and colleagues’
481 findings. However, a real break in the series occurs in November-December
482 2009. This is expected since this period coincides with the time when emails of
483 researchers from the Climatic Research Unit (CRU) at the University of East
484 Anglia were hacked, uploaded to the Internet, and subsequently scrutinized by
485 climate sceptics. Following this flurry of attention to scientific integrity during
486 late 2009 and early 2010, a downward trend then follows with significant peaks
487 occurring in July 2010 when the Independent Climate Change Email Review
488 was released and December 2011 which was just after a second round of CRU
489 emails were uploaded to the Internet; an incident named “climategate II” by
490 climate sceptics.

491 Overall, the evidence in Figure 2 suggests that the data produced by the
492 model vary in predictable ways based on closely related external events and, as
493 such, exhibit adequate levels of predictive validity. Moreover, in the interest of
494 space, we limited our discussion to two key topics in the area of climate policy
495 and science. However, many other topics—such as extreme weather, interna-
496 tional negotiations, and energy policy—display similar patterns of predictive
497 validity.

498 *5.3. Assessing concurrent validity via a human “gold standard”*

499 As a last look at validity, we compare the model’s classifications to those of
500 two human coders using a random sample of 300 manually annotated documents.
501 After ensuring a suitable level of inter-coder reliability (Krippendorff’s $\alpha = 0.74$),
502 the coders classified the primary topic or theme of each article using either the
503 47 categories provided in Table 2 or “other” if none of the model-based topics
504 suitably captured the main theme.² Based on these data, the micro-averaged
505 precision and recall for classifying the primary topic are 0.64 and 0.65, respec-
506 tively. These figures are encouraging, as coding a document into 47 categories
507 is a difficult classification task and the model performs considerably better than
508 rolling a 47 sided die or simply choosing the modal value. More importantly
509 for the analysis below, aggregating the topics to produce more general themes
510 or classes greatly improves each measure of performance. When aggregating all
511 the way up to the science label used in Section 6, the precision and recall are
512 0.94 and 0.96, respectively; for the policy label, the precision and recall are 0.94
513 and 0.92, respectively..

514 It is also important to note that assessing a topic model using only the
515 primary topic offers a conservative estimate of performance. Several distinct
516 themes often contribute to a document’s composition and deciding which is

²The coders consisted of one author and a research assistant. In the pilot phase, to get a general sense of the coding task, each coder carried out an initial coding of 10 randomly selected documents, which was followed by an in-depth discussion of coding choices. Following this initial round, the coders went on to code an additional 30 documents and the discussion was repeated. Finally, the coders went through a random sample of 50 documents—this is the sample used to calculate inter-coder reliability.

517 “primary” is often quite difficult for both human and machine. Indeed, allowing
518 documents to be composed of multiple topics—an appropriate assumption for
519 the vast majority of texts in our corpus—is one of the major advantages of using
520 the LDA. Notably, the proportion of documents correctly classified jumps to
521 0.78 if one considers the first two most probable topics based on the model.

522 6. Policy versus science: Is the era of science denial over?

523 In 2013, the World Wildlife Fund-UK’s chief advisor on climate change, Leo
524 Hickman, stated in no uncertain terms that “[t]he real world is leaving behind
525 those who flatly reject the science underpinning the notion that anthropogenic
526 greenhouse gas emissions are warming the planet,” arguing that climate science
527 sceptics are being replaced by “climate policy sceptics.” More recently, in July
528 2015, Elliott Negin from the Union of Concerned Scientists pointed to a more
529 modest retreat: “[deniers] now concede that climate change is real, but reject the
530 scientific consensus that human activity—mainly burning fossil fuels—is driving
531 it.” These arguments are not new. Speculation regarding the decline of scientific
532 scepticism is seen as early as 2002, just two years after McCright and Dunlap’s
533 seminal study. In a leaked memo to the Republican party, conservative strategist
534 Frank Luntz suggests:

535 *The scientific debate remains open. Voters believe that there is no*
536 *consensus about global warming within the scientific community.*
537 *Should the public come to believe that the scientific issues are settled,*
538 *their views about global warming will change accordingly. Therefore,*
539 *you need to continue to make the lack of scientific certainty a pri-*
540 *mary issue in the debate, and defer to scientists and other experts*
541 *in the field [...] The scientific debate is closing [against us] but not*
542 *yet closed. There is still a window of opportunity to challenge the*
543 *science.*³

544 If indeed the window of opportunity for scientific scepticism has closed, this
545 would be a welcome development for proponents of climate action. After all, a
546 general acceptance of anthropogenic global warming is a necessary condition for a
547 comprehensive agreement on climate change mitigation and there is considerable
548 evidence to suggest that acknowledging the scientific consensus on AGW predicts
549 support for climate policy (Ding et al. 2011, McCright et al. 2013, van der Linden
550 et al. 2015). However, based on existing evidence in the literature, it is difficult
551 (if not impossible) to discern whether the era of climate science denial is truly
552 over or if the organised denial of “junk” science remains alive and well.

553 To examine this question, we present evidence on the evolution of the CTT
554 science- and policy-related discourse since the late 1990s. Figure 3(a) presents

³Italics are in original. The full text of the environmental policy section of the Luntz memo can be accessed at https://www.motherjones.com/files/LuntzResearch_environment.pdf.

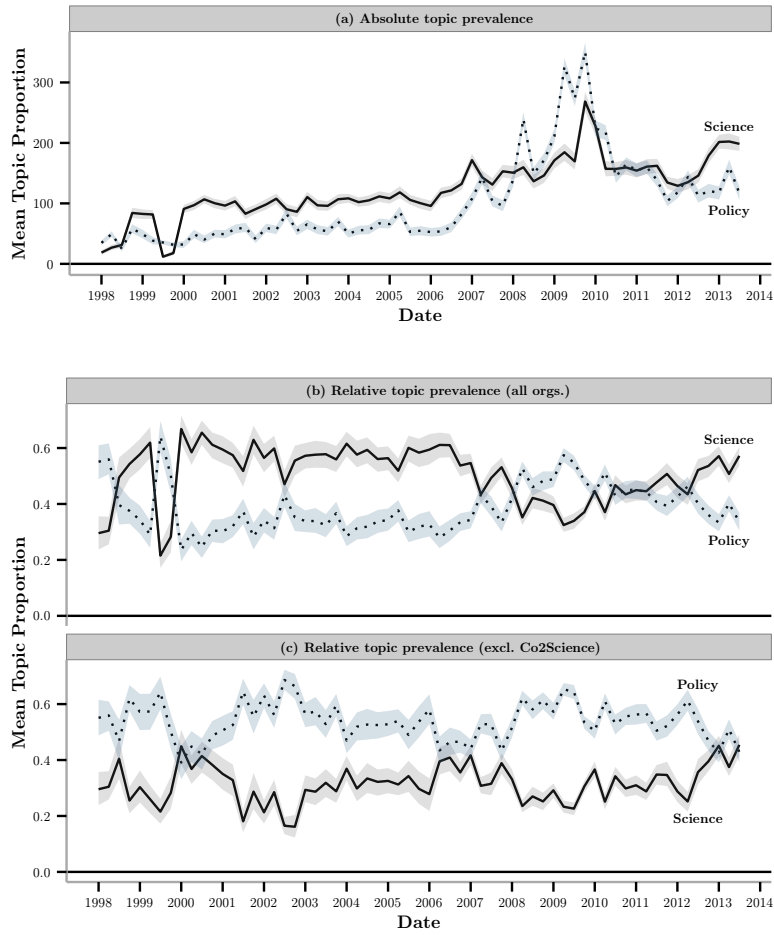


Figure 3: *The evolution of political and science-related discourse.* Panel (a) displays the summed quarterly topic probability of “science” (solid) and “politics & policy” (dotted) related themes for all CTTs in the sample over the period January 1998 – August 2013. These categories are aggregations of the topics based on the codings displayed in Table 2. The bottom panel shows the average quarterly topic probabilities—a relative measure—for the same categories; (b) uses all available data, while (c) excludes Co2Science. The areas around each series represent the bootstrapped 95% confidence interval.

555 the sum of the topic proportions for “science” and “politics & policy” related
556 topics for each quarter over the Q1/1998–Q3/2013 period (absolute measure),
557 while Figures 3(b) and (c) provide mean topic probabilities (relative measure).
558 Each time series also includes an estimate of uncertainty, as measured by a
559 bootstrapped 95% confidence interval.⁴ These categories are aggregations of
560 topics following the codings presented in Table 2. Several aspects of Figure 3 are
561 noteworthy. First, in absolute terms, the intensity of discussion—regardless of
562 whether the focus is on “science” or “politics & policy”—has grown considerably
563 since McCright and Dunlap (2000). Consistent with broader trends in media
564 coverage of climate change, (e.g. Schmidt et al. 2013), the discussion increases
565 until around the time of the Copenhagen conference and the so-called climategate
566 scandal (late 2009–early 2010), and then declines thereafter. Moreover, these
567 data suggest that science-related discussions have been dominant since 2012.
568 We thus find little evidence for the “end of science denial” and yet a rise in
569 “policy sceptics” remains consistent with the data.

570 Second, as demonstrated in Figure 3(b), recent years are marked by a di-
571 vergence between the science and policy series: the relative emphasis on science
572 seems to be gaining in the post-“climategate” era. Nevertheless, this result is
573 largely driven by the influence of one prolific science-oriented CTT, Co2Science,
574 which produces a steady stream of scientific review articles (see Table 1). When
575 excluding this organization, as shown in Figure 3(c), we see that policy-related
576 discussion is frequent, there has been convergence between the frequency of
577 policy and science discussion at key periods, and that aggregate discussions of
578 science appear to be on the rise after 2012.

579 However, aggregating across diverse science and political themes, as shown
580 in Figure 3, masks important heterogeneity in sceptical discourse. Some or-
581 ganizations focus almost entirely on producing science-oriented content (e.g.,
582 Co2Science), others are dedicated to addressing issues surrounding climate pol-
583 icy (e.g., the Heritage Foundation), and still others focus on a range of both
584 science and policy related topics. In the later category, the Heartland Insti-
585 tute stands out as an important counter-movement organisation worthy of a
586 closer look. As proudly trumpeted on its website, Heartland has been described
587 by mainstream news sources as “the world’s most prominent think tank pro-
588 moting scepticism about man-made climate change” (The Economist) and “the
589 primary American organization pushing climate change scepticism” (The New
590 York Times). These “accolades” are not by chance. Judging from our data (see
591 Table 1), it is clear that Heartland has been a front-runner in CTT literature
592 production and has been a leader in public outreach. Indeed, Heartland has been
593 recognized by scholars as a significant contrarian actor and has been prominently
594 studied in past literature on organised climate scepticism (McCright and Dunlap

⁴Note that to remain as consistent as possible with the assumed data generating process, we conducted the bootstrap at the *document* level for each time period of interest in the sample. Specifically, for a given quarter, we sample (with replacement) from the available documents and calculate topic prevalence, repeating this process for 1,000 replicates for each series.

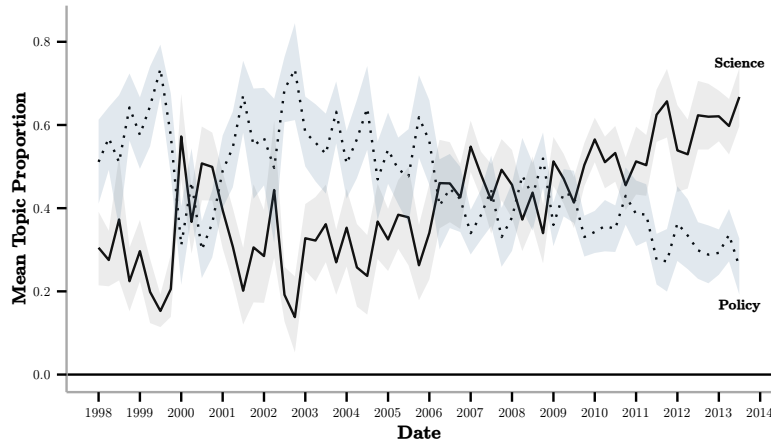


Figure 4: *The Heartland Institute’s political and science-related discourse.* Displays average quarterly topic probabilities for science- and policy-related themes in documents disseminated by Heartland over the period January 1998–August 2013.

595 [2003, Cann 2015](#)).

596 How then, does its discourse on “science” and “politics & policy” related
 597 themes compare to the general trend illustrated in Figure 3? We narrow our
 598 focus on Heartland in Figure 4, which shows how beginning in 2002, we can
 599 observe a steady rise in an emphasis on topics related to science, as well as an
 600 attendant decline in policy-oriented themes. Interestingly, Heartland’s shift to-
 601 wards science-related themes preceded “climategate” by more than 7 years and
 602 actually dovetails with Luntz’s famous “Straight Talk” memo. It is therefore not
 603 a surprise that for a decade it has organized the annual International Conference
 604 on Climate Change (also known as Denial-a-Palooza) which serves as a forum
 605 for climate science deniers,⁵ or that it made headlines in 2012 after launching a
 606 controversial ad campaign which equated climate scientists with Ted Kaczynski
 607 (the Unabomber). The consistent trade-off of attention from policy to science
 608 since 2002 suggests that Heartland has invested heavily in attempting to re-open
 609 the “window of science scepticism.”

610 Another potential source of heterogeneity relates to our categorizations of
 611 science and policy related discussions. It is clear that some topics labelled as
 612 “policy” are only tangentially related to “climate” policy and that there are im-
 613 portant differences between climate science and scientific integrity. We therefore
 614 examine three themes which are directly related to climate science and policy:
 615 “Science,” “Scientific Integrity,” and “Energy and Emissions Policy.” Figure 5

⁵<http://www.desmogblog.com/directory/vocabulary/2782>

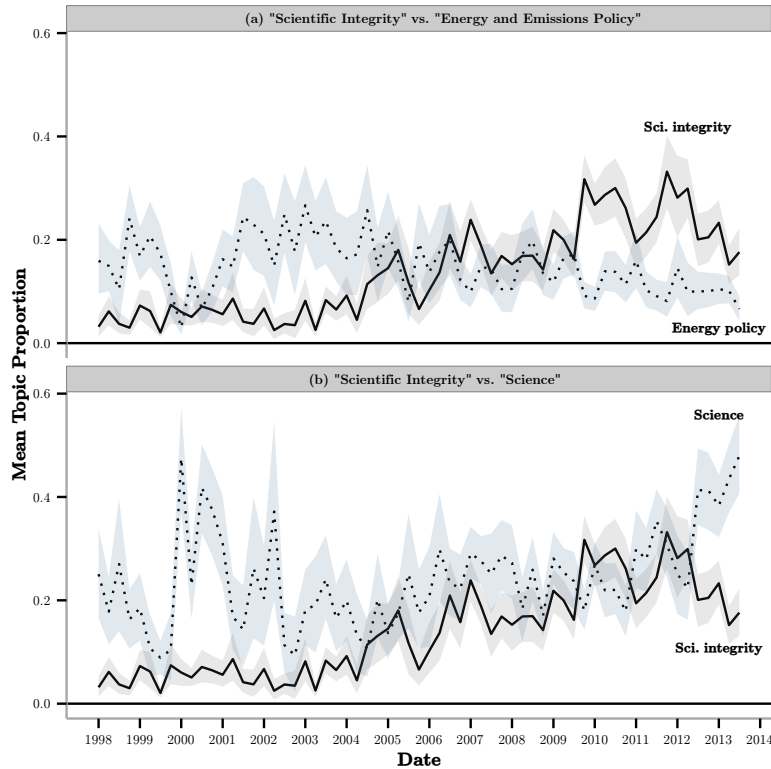


Figure 5: *Climate-specific related themes over time.* The figures show the average quarterly topic proportions of three topic clusters, which are directly related to climate science and policy, as classified in Section 5.1: “Science,” “Scientific Integrity,” and “Energy and Emissions Policy.” Note that Co2Science has been excluded from this analysis. The series covers the period Q1/1998–Q3/2013.

616 provides the results of this comparison. Several features of this figure are notable.
 617 First, considering the “Scientific Integrity” series, there has been an appreciable
 618 rise in the prevalence of integrity-related topics starting in 2004 and peaking in
 619 2011. Second, talk of scientific integrity began to overtake that of energy policy
 620 during 2006 and 2007—which corresponds to a period dominated by *An Inconve-*
 621 *nient Truth* and Al Gore’s acceptance of the Nobel Peace Prize—and proceeded
 622 to become relatively more prevalent in the post-“climategate” era (Figure 5 (a)).
 623 Lastly, while the discussion of climate “Science” was more frequent relative to
 624 “Scientific Integrity” from 1998 to roughly 2004, the two series become inter-
 625 twined for much of the sample period. This suggests that CTTs were just as
 626 likely to question the integrity of individual scientists and scientific bodies than
 627 to discuss alternative scientific viewpoints; though, there has been a percepti-

628 ble break since 2012, with discussions of “Science” once again dominating the
629 conversation.

630 7. Conclusion

631 Despite urgent calls to action among climate scientists, the U.S. government
632 continues to avoid comprehensive climate policy action and the American public
633 remains misinformed on key aspects of the debate. A growing literature draws at-
634 tention to the influence of a well-organized and well-funded movement of climate
635 sceptics. This study provided the first systematic update of the claims making
636 activity of conservative think tanks—a critical piece of the climate counter-
637 movement—since the influential work of [McCright and Dunlap \(2000\)](#). Our key
638 findings include:

- 639 1. The overall level of CTT claims-making has grown rapidly over the past
640 decade and a half, reaching a peak during late 2009–early 2010;
- 641 2. The 19 CTTs studied address a wide range of topics in their written com-
642 munication since [McCright and Dunlap \(2000\)](#), which cluster into distinct
643 themes associated with politics, policy, science, and scientific integrity;
- 644 3. Topics questioning the integrity of individual scientists and scientific bodies
645 appear closer (semantically) to politics than science, suggesting that claims
646 often considered the hallmark of scientific scepticism are rooted in politics;
- 647 4. The era of climate science denial is not over. While the aggregate re-
648 sults demonstrate that both policy and science discussions remain stable
649 throughout the period of study (Figure 3), a detailed analysis of a criti-
650 cal CTT (Figure 4) and a focus on climate change-specific themes (Figure
651 5) reveal the increased importance of both science and scientific integrity
652 discussions over the sample period.
- 653 5. CTTs tend to react to the external environment—i.e., they *counter* claims—
654 and thus studies focusing on narrow intervals of time (or a single organi-
655 sation) are likely sensitive to these contextual factors.

656 It is important to note, however, that the current study has a number of lim-
657 itations. First, we are necessarily restricted to the documents that are publicly
658 available online. It should be noted, however, that these organisations have an
659 incentive to distribute what they produce, which could support validity, but this
660 tendency may be weaker for documents produced further back in time. Second,
661 we do not transcribe video and audio data, which may be included in future
662 work. Third, and more importantly, we do not perform any sentiment analysis
663 on the corpus. For instance, if a document focuses on the Medieval Warm Pe-
664 riod (topic 37), we are assuming that its argument is that natural forces have
665 a stronger climate impact than human activity. Based on our reading of the
666 corpus, as well as our theoretical priors, this is a plausible assumption. Despite
667 these limitations, in providing this corpus to the community, we hope to offer a
668 platform for future work on the claims-making activity of CTTs.

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