Supplementary Materials for Who Securitizes? Climate Change Discourse in the United Nations

December 11, 2020

Contents

Speech Data

The data used in this analysis is pre-processed by a text tiling procedure, which identifies features to divide speeches into substantively coherent units ("segments") that are analogous to paragraphs (Hearst, 1997). This procedure is necessary because in many of the documents, natural paragraph delimiters are not available and formatting indicators (i.e. line breaks) are inconsistent across units, so semantic similarity is used to determine paragraph-like units.

After separating the speeches into segments, I extract the speeches on climate change from the full corpus by identifying paragraphs that contain any of a set of keywords, shown in Table 1. The set of key terms was composed in several stages. I began with words that appeared frequently in the context of climate change discussions in the course of my research. I then expanded the set of key words by iterating on the initial set, finding the words whose occurrence correlated the most highly with the initial set and were substantively related to climate change. These discovered words were added to the initial set to create the final set of filtering words.

Table 1: Terms Used to Create Climate Filter

1	climate change	7	climate politics	13	global average temperature
2	global warming	8	framework convention on climate change	14	greenhouse effect
3	cap and trade	9	bali roadmap	15	kyoto protocol
4	unfccc	10	bali action plan	16	ipcc
5	paris accord	11	greenhouse gas	17	greenhouse effect
6	emissions trading scheme	12	ghg	18	intergovernmental panel on climate change

Descriptive statistics of the full corpus and the climate subset are shown in Tables 2 and 3. The overall length of speeches declines over time, dropping off particularly steeply after 2000. In any speech, the greatest number of segments that specifically discuss climate change is 16 (a speech by Samoa in 2015), while the average is 4 segments. SIDS discuss climate change at higher rates than other states with more paragraphs about climate change and greater speech proportions on the topic, but they are not necessarily early adopters, picking up the climate discourse at the same time as other states. There are few outliers in terms of speech length: one exceptionally long speech was given by Libya in 2009 (100 segments). Only four other countries gave more than one speech longer than 50 segments (Russia, USA, Cuba, and Germany), and multiple long speeches were given in 1973, 1976, 1978, 1983, 1984, and 2009.

Table 2: Descriptive Statistics: All Segments

	# Segments per Speech	# Speeches per Year	Avg. # Segments per Year	Total Segments by Year	Avg. Segments Per Country
Min.	4	150	17.1	2963	11.2
1st Qu.	15	191	19.1	3271	22.6
Median	19	193	20.8	3552	28.0
Mean	20	191	20.9	3565	27.6
3rd Qu.	23	194	21.2	3662	31.9
Max.	93	196	40.4	5550	51.9

To prepare this speech data for unsupervised text analysis, additional pre-processing steps were needed. I remove word stems that occurred in fewer than 1% of documents

Table 3: Descriptive Statistics: Climate Segments Only

	# Segments per Speech	Prop. of Speech	# Speeches per Year	Avg. # Segments per Year	Total Segments per Year	Avg. Segments per Country
Min.	1	0.01	1	1.0	1	1.0
1st Qu.	2	0.09	125	3.3	270	2.3
Median	3	0.16	147	3.8	360	3.1
Mean	4	0.19	126	3.5	315	3.6
3rd Qu.	5	0.26	157	4.1	404	4.3
Max.	16	0.73	169	4.4	492	8.3

or in more than 95% of documents, common stop words, as well as documents that contained only unique word stems (that is, shared no features with other documents). I also remove the terms 'united', 'nations', 'general', and 'assembly', as these will occur too frequently to be informative.

Topic Models

Methodology and Estimation

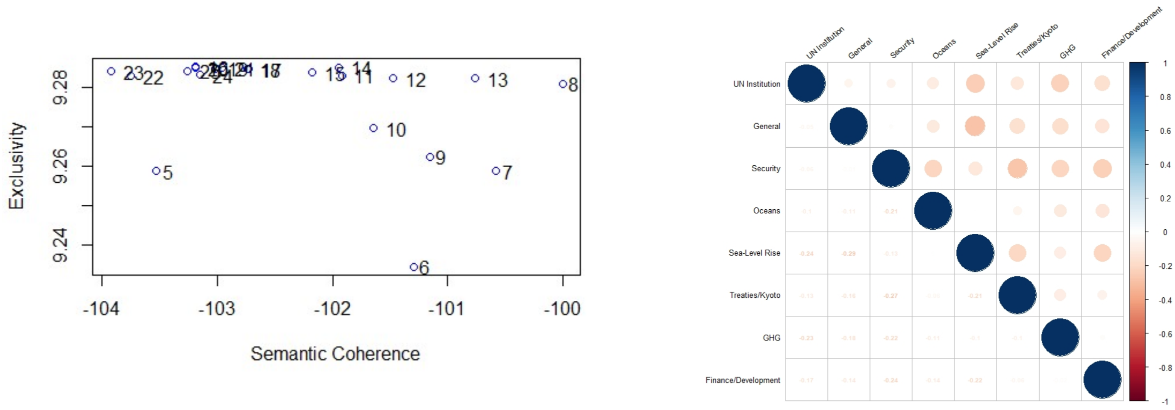
LDA, and the STM variant of LDA employed in this analysis, assumes a hierarchical system of distributions, with an underlying Poisson distribution of words (N) and of Dirichlet topic probabilities ( ) across topics (k). Conditional on these priors of words and of topics, each of N words in a document w_n is drawn, and each topic z_n and word w_n from a Multinomial. The parameter is a KxV matrix of word probabilities (Grimmer and Stewart 2013). STM adjusts this the LDA procedure to allow the topic proportions of (referred to as topical prevalence) and the observed words n (referred to as topical content) to be drawn from a document-specific prior rather than a universal prior. Covariates associated with each document can inform the distribution of topics and words across documents (Roberts et al. 2016). To allow for variation in the content and prevalence of topics over time, I include year as a parameter in the STM. To allow the prevalence of topic to vary non-linearly over time, I fit a spline on years in topical prevalence. To allow topical content to vary over time but to impose some constraint, I fit a factor on decade in topical content.[1]

I estimate the STM models at the standard value value of the prevalence hyperparameter ( ) as $1{=}k$, though changing the value of had little effect on the results. I employ a Spectral initialization for stability. Because the corpus is already limited to the particular topic of climate change, I employ a smaller k than would be typical for analysis across an entire corpus. I test values of k ranging from 2 to 15 and assess topical coherence manually to find the optimal number of topics. I estimate the STM with $k = 8$ topics based on manual evaluation of topical coherence, as well as maximization of semantic coherence and exclusivity, seen in Figure 1. The distinctiveness of the different topics obtained in the final model is validated by an analysis of the correlation between the different topics, which was found to be low across all topical pairs (Figure 2). The ultimate topics obtained were quite consistent across all the different model specifications described above.

[1] Results were largely consistent across different parameterization choices of year and decade; the final modeling choices were made to minimize the residuals in the model.

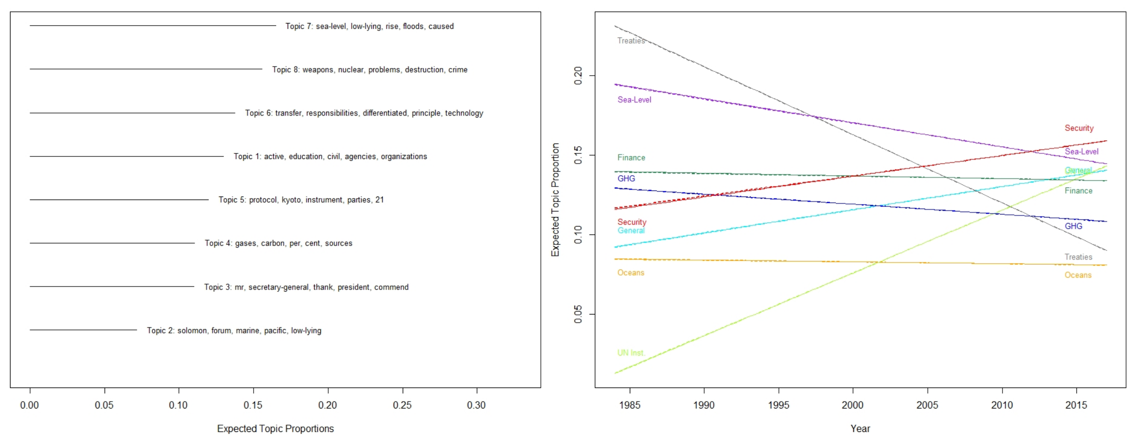
The topic proportions are shown in Figure 3 and Table 1 of the main text. The existential threat topic is the second most frequently employed. It is also used more over time, while other frames, particularly the Kyoto Protocol frame, decrease in their use over time (Figure 3, right panel). Across all time periods, the P5 employ the language of existential threat more than do SIDS (Figure 4)

Figure 1: Selecting Number of Topics



Note: Number of topics (*k* was chosen to maximize semantic coherence and exclusivity (left), to minimize correlation between topics (right), and based on best performance under manual examination.

Figure 2: Topic Proportions

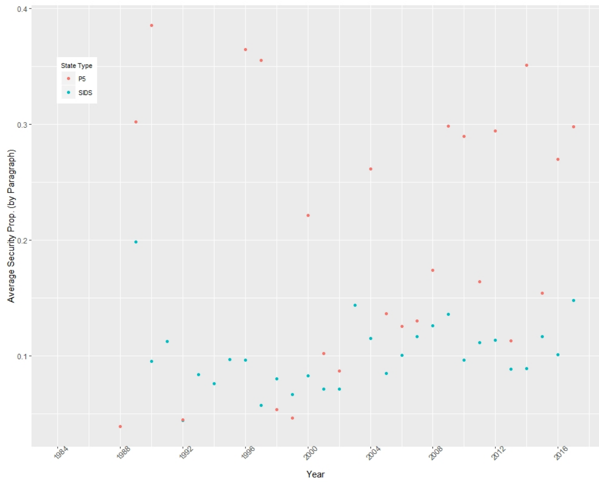


Note: Left panel shows expected topic proportions across the corpus, right panel shows linear estimation of changing topic proportions over time.

Robustness

I validate the results of the STM with a supervised analysis. I randomly selected 10% of the speech paragraphs on climate change (448 paragraphs) and read them to

Figure 3: P5 Speak Existential Threat More Than SIDS Across Time



identify the topics that they employ, coding them as being security relevant or not. In this exercise, I was also able to test the keyword filtering approach, verifying that there were no false positives (that is, there were no speeches included in the data that were not actually about climate change). Based on my binary coding of the paragraphs as security-relevant or not, I found a high level of agreement with the results of the STM. When the results of the STM are binarized at the level of the mean (paragraphs with 15% or higher topical prevalence in the existential threat topic are coded as security-relevant), my coding agreed at 58%. When the results of the STM are binarized as more than half of the paragraph identified as the existential threat topic, my coding agreed at 67%. This provides confidence that the results of the unsupervised analysis are not artifact but are indeed identifying clusters of security language in the data.

Based on the words found to be most representative of the different topics (words within each topic with the highest topic-word probability,), I constructed the label for each. These labels were validated with a crowdsourcing exercise whereby anonymous respondents were shown the set of words representing each topic. Respondents were asked to provide a one word that best summarized the content. For the security topic, the words presented in the task were "weapons, nuclear, problems, destruction, crime, war, mass, threats, hunger, conflict, today, diseases, live, terrorism, still, life, crises, values, increasingly, complex." Out of 16 respondents (10 non-political scientists and 6 political scientists), 10 provided words that corresponded with my characterization of the topic ("security, crises, war, weapons of mass destruction, fighting, war and terrorism, conflict, international conflict, war, threat"), while the remaining 6 respondents provided more general words ("Middle East, international relations, human influence, changing society, foreign policy, fear"). There were no noticeable differences in responses across political scientists from others.

Predicting Securitization

Variables

P5: Indicator for P5 Member status (United States, United Kingdom, China, Russia, and France).

E10: Indicator for elected UNSC membership status during the years when a state served on the UNSC (Dreher et al. 2009).

SIDS: Indicator for UN designation as a small island developing state (Cuba, Dominican Republic, Haiti, Singapore, Trinidad and Tobago, Fiji, Guyana, Jamaica, Mauritius, Barbados, Bahamas, Grenada, Comoros, Cabo Verde, Guinea-Bissau, Maldives, Papua New Guinea, Sao Tome and Principe, Suriname, Seychelles, Samoa, Dominica, Saint Lucia, Saint Vincent and the Grenadines, Antigua and Barbuda, Belize, Solomon Islands, Vanuatu, Saint Kitts and Nevis, Micronesia, Marshall Islands, Palau, Nauru, Tonga, Tuvalu, Kiribati, Timor-Leste).

Public Concern: This data comes from the 2010 Gallup World Poll conducted across 106 countries in 2010 that featured two questions on climate change (Gallup 2010). The first survey question measured ***understanding***, asking respondents "How much do you know about global warming of climate change?" and coding understanding as the percentage of respondents saying they know something or a great deal. The second question measured ***concern***, asking respondents "How serious of a threat is global warming to you and your family?" and coding concern as the percentage of respondents reporting that they view global warming as a very or somewhat serious threat. This question was only asked to respondents reporting familiarity with the topic of climate change. The panel included all of the P5 members except France, as well as 4 SIDS (Singapore, Dominican Republic, Haiti, and Comoros, out of 37 total SIDS).[2] I use the measure of concern rather than understanding in the model because it more closely capture the kind of electoral pressure that would be likely to move policymakers to advance the issue of climate change on the global agenda.

Democracy: I use scores from the Polity IV project to indicate regime type (Center for Systemic Peace 2018). Polity scores can take on a possible range of -10 to 10. Countries with Polity scores greater than 6 are coded as democracies, while countries with Polity scores less than -6 are coded as autocracies.

Climate Disasters: I construct a measure of climate disaster occurrences to capture the experienced effects of climate change across states, utilizing data from the International Disaster Database from 1984-2018 (Guha-Sapir 2015). I collect data on climate-related disasters, including climatological (drought and wildfire), hydrological (flood and landslide), and meteorological (extreme temperature and

[2]Respondents in P5 states show higher understanding than either other states or SIDS (0.85 for the P5, 0.54 for SIDS, and 0.68 for other states). For both the P5 and SIDS the level of concern is less than other states (0.43 and 0.44 for the P5 and SIDS compared to 0.50 for other states). On both measures, China is substantially lower than other P5 members, while Singapore is substantially higher than other SIDS.

storm). The disaster database captures the number of deaths, injured, affected, homeless, and costs for many of these events. To maximize data availability and reduce the effects of income-dependence, I follow Roberts and Parks (2007) and use a smoothed measure of total persons affected. For each country, I sum the number of total persons affected by climate disasters and divide by the country population in each year and then take the log.

Amount Warming: I measure warming as a change in national average air temperature over land since 1960 in degrees Celsius, measured by Berkeley Earth (2020). This measure ranges from 0.65 degrees to 3.6 degrees, with a mean of 1.88 degrees.

Agreement: The measure of affinity is constructed by Bailey, Strezhnev and Voeten (2017). These measures of state preference similarity are constructed using voting records in the UNGA. The voting similarity index compares one country's voting record in a given year with another, ranging from 0-1. The main model includes the measure of voting agreement with the US. I also specify models where this measure is replaced for vote similarity with Brazil and with India to determine whether coalitions of developing countries are influential in setting the patterns of securitization discourse.

Military Expenditures: Military expenditures as a proportion of GDP, measured by the World Bank Development Indicators (World Bank 2020).

Aircraft Carriers: Indicator for countries with aircraft carriers. Countries included are Argentina, Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Netherlands, Russia, Spain, Turkey, Thailand, United Kingdom, and United States. This binary measure specifies countries that have operated aircraft carriers at some point in history. All P5 members are included as naval powers.

GDPPC: Annual measures of country level gross domestic product per capita (logged), measured by the World Bank Development Indicators (World Bank 2020).

Population: Population (logged), measured by the World Bank Development Indicators (World Bank 2020).

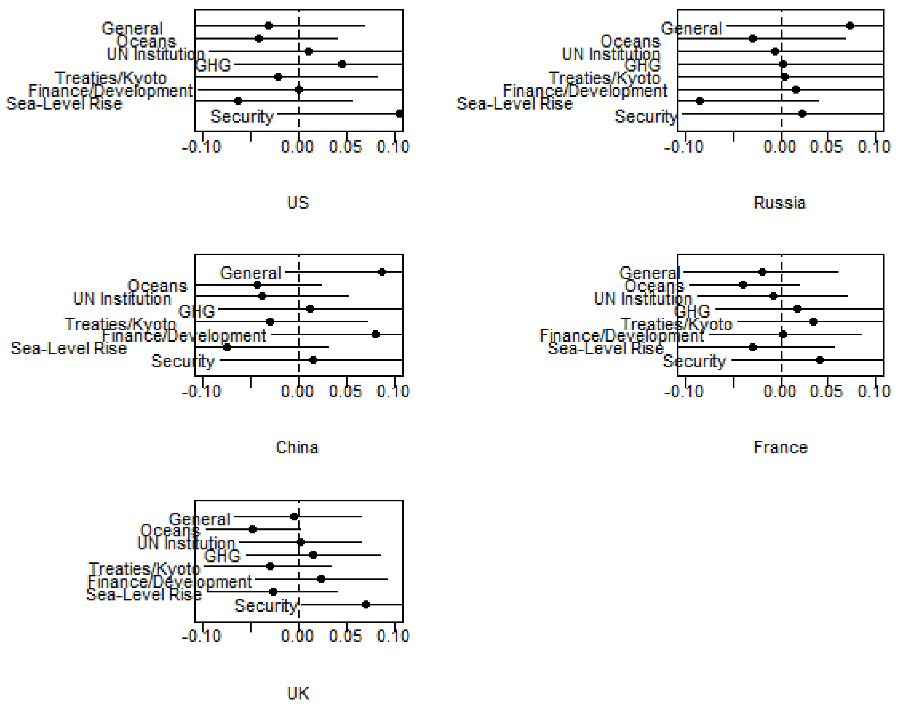
Robustness

The results in the main model show linear regression estimates with standard errors averaged from 5 imputations of missing data, conducted with Amelia. These results are also observed in simulated first differences (Table 4). The main result that the P5 securitize more than other states holds for each P5 member directionally, although because of the reduced amount of data, the results do not hold statistical significance at the individual level (Figure 4). As discussed in the main paper and shown in Table 2 of the main text, I find that the results are robust to many different specifications. In addition to these primary robustness tests, I also conduct a placebo test. I also examine trends in securitization across the whole General Debate corpus and find that securitization is not a discourse-wide trend: the security topic (Topic 1) is the least frequently discussed topic in the overall discourse (Figure 6). The rate of security language across the whole corpus is declining over time (Figure 7). Security words are not characteristic of other topics. In the full corpus, the P5 are also not more likely to use the general security frame more than non-P5 (Figure 8), indicating that this trend is specific to climate discourse.

Table 4: First Differences on Changing P5 and SIDS Status

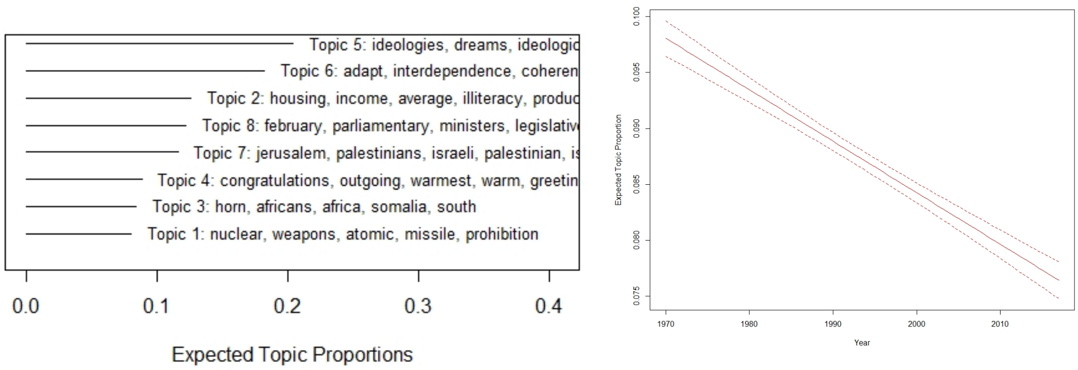
	P5 Ind	SIDS Ind
Mean	0.051	-0.080
St. Dev.	0.024	0.012
2.5 CI	0.005	-0.104
97.5 CI	0.097	-0.057

Figure 4: P5 States Individually Securitize



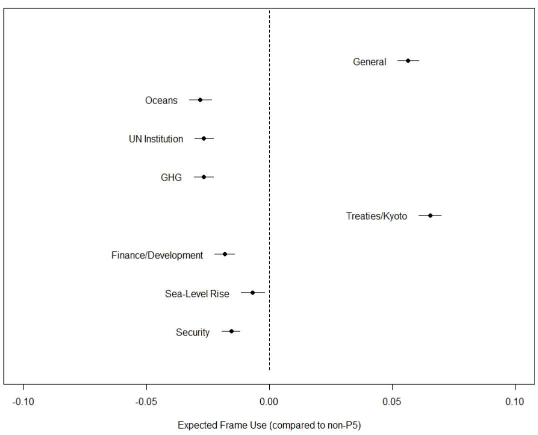
Note: Figures show expected speech segment proportion in the existential risk topic estimated by STM, comparing each P5 states to other states. Uncertainty calculated from the STM by composition with 95% confidence intervals.

Figure 5: Security in Placebo Test



Note: Left panel shows expected topic proportions across the corpus, right panel shows linear estimation of changing security topic proportion over time.

Figure 6: P5 Do Not Speak Security More Than Non-P5 in Placebo



References for Supplementary Materials

1. Bailey, Michael A., Anton Strezhnev, and Erik Voeten. 2017. Estimating Dynamic State Preferences from United Nations Voting Data. *Journal of Conflict Resolution* 61(2), 430–456.

2. Dreher, Axel, Jan-Egbert Sturm and James Vreeland. 2009. Development Aid and International Politics: Does membership on the UN Security Council influence World Bank decisions? *Journal of Development Economics* 88: 1-18 2009.

3. Berkeley Earth. 2020. Global Warming by Country.

4. Gallup. 2010. Gallup World Poll.

5. Grimmer, Justin, and Brandon M. Stewart. 2013. Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis* 21.3: 267-297.

6. Guha-Sapir, D. EM-DAT: The Emergency Events Database. 2015.

7. Hearst, Marti A. 1997. TextTiling: Segmenting Text into Multi-Paragraph Subtopic Passages. *Computational linguistics* 23.1: 33-64.

8. Center for Systemic Peace. Polity IV Annual Time-Series, 1800-2018. 2019.

9. Roberts, J. Timmons, and Bradley Parks. *A Climate of Injustice: Global Inequality, North-South Politics, and Climate Policy.* MIT Press.

10. Roberts, Margaret E., Brandon M. Stewart, and Edoardo M. Airoldi. 2016. A Model of Text for Experimentation in the Social Sciences. *Journal of the American Statistical Association* 111.515: 988-1003.

11. World Bank. 2020. World Development Indicators.