# Appendix for "The textual dynamics of international policymaking: A new corpus of UN resolutions, 1946-2018"

April 15, 2024

## Contents

# 1 Detailed Methodology

## 1.1 Feature Extraction

First, I extracted all references to other UNGA and UNSC resolutions from each text. References to other resolutions follow a prescribed style, invoking the title of the relevant document (e.g., "A/RES/62/215," which refers to the 215th resolution adopted by the General Assembly in its 62nd session). Because the references follow a systematic pattern, I can employ automatic procedures to identify them, using regular expressions to extract references from each text. This process allows us to capture variations in reference formats over time (including such varied formats as "1970 (XVIII)" and "S-RES-479"). I then cross-referenced this list of extracted references against a master database of resolutions for each point in time to validate the results. I also removed all self-reference, that is, occasions when the reference refers to the current resolution.

Second, using a structural topic model (Roberts et al. 2014), I extracted *topic proportion vectors* for each document in the corpus. After testing several specifications to maximize semantic coherence and exclusivity, as well as manually evaluating the performance of the different models, I select a specification with 50 topics. I employ a spectral initialization and a 10 iteration burn-in period. Prevalence and content of topics are allowed to vary nonlinearly over time, which is critical given that topics on the UN agenda change in prevalence over time (for example, climate change gains in prevalence over time, while colonial conflicts decline). To label the topics produced by the model, I read the top ten highest-probability words and the top twenty documents with the largest proportion of their content assigned to that topic and inductively constructed topic labels. I then extracted the topic label associated with the highest-probability topic for each document, which I used as the primary content label for each document in the corpus. For 92.5% of reference pairs in the dataset, the topic label of the resolution matched the modal topic label for the resolutions referenced by that document. Since these references were not part of the input data for the topic model I fit, this result suggests that the topic model I estimate is identifying similar topics to those identified by the references I extract. I normalize the number of references in each topic area by the number of resolutions in the topic area to better capture the *rate* of referencing within resolutions independent of the number of resolutions adopted.

Third, I identified instances of textual alignment in the corpus. Following Linder et al. (2020), I use the topic proportion vectors I extracted previously to calculate pairwise Hellinger similarity values between the topic proportion vectors for each unique pair of documents. For each document, I identified the documents with the top 500 similarity values, and extracted maximally-aligned sequences of text—and corresponding alignment scores—using the Smith-Waterman alignment (SWAlign) algorithm. SWAlign is preferred to standard plagiarism detection approaches because of its scalability and its ability to implement adaptively-sized editing differences between texts. SWAlign is a sequence alignment algorithm that allows users to identify sequences of shared elements in an ordered list, with user-defined tolerances for gaps or mismatches. Specifically, I find the optimal local alignment for each document, with alignment parameter set to 2 and mismatch/gap parameters set to -1. Finally, I weight each alignment score by the distinctiveness of the tokens contained in each alignment, to downweight common, "boilerplate" recycling (Wilkerson, Smith, and Stramp 2015).

## 1.2 Topical Dispersion

To measure topical dispersion within each chamber, I calculate normalized informational entropy, a standard measure of dispersion that ranges from 0 (least dispersed) to 1 (most dispersed), and then use the "effective topics" transformation, which represents the number of equiprobable topics needed to produce a given entropy value (Shaffer 2017). Normalized informational entropy is defined as $H(X) = -\frac{1}{ln(n)} \sum_{i=1}^{n} X_i log(X_i)$. I observe an informational entropy value of 0.95 for UNGA resolutions, compared with an informational entropy value of 0.75 for UNSC resolutions. The "effective topics" for a topic proportion vector of length $n$ with entropy $\eta$ is $k = n^{\eta}$. For the UNGA, this transformation returns a value of 41.1, indicating that UNGA resolutions are almost equally split across all topics. By contrast, UNSC resolutions contain 18.8 effective topics, indicating that a topic proportion vector containing approximately half the number of equiprobable topics would produce an equivalent entropy value to the one observed.

# 2 Descriptive Statistics:

## 2.1 References and Resolutions

Both the UNGA and UNSC exhibit increased rates of referencing over time, as well as increasing numbers of references included in each resolution. Intuitively, this makes sense, as the universe of prior resolutions and thus material to refer to increases over time. Referencing rates are more variable in the UNSC than the UNGA over time, which is likely due to the more flexible institutional nature and small number of negotiating parties in the UNSC, leading to more flexible working norms. Patterns in resolution and reference rates over time are illustrated in Figures 1, and 2. Annual references, even when normalized by the number of resolutions, particularly increase in the 1990s. This finding is also intuitive, as the 1990s were an extremely active period of legislation in the UN, as Cold War politics no longer precluded consensus between the United States and the Soviet Union/Russia. This pattern is exhibited in both chambers, but is more pronounced in the UNGA.

In general, the data consists of many unique citations, and it does not appear to be the case that the main results are driven by the same set of citations being included in document dyads. For example, I observe that among the highly aligned document pairs, the median number of shared citations common to both documents is 9 (with an average of 12) and the median number of unique citations in each of the documents is 3 (with an average of 5).

To get a sense of the distributional dimensions of citations, I can compare this to document pairs at the different important similarity cutoffs. For document pairs at the median level of similarity: in these cases, the median number of shared citations among the pair is 0, with an average of less than 1. In these pairs, there are 7 unique citations in each document of the pair. At the 25th percentile of similarity, the results are similar to those at the median level of similarity. For pairs at the 25th percentile of similarity, the median number of shared citations in a pair is 0 (average less than 1), and there are 6 unique citations in each document (average 7).

## 2.2 Topical Variation

I identify topics using a structural topic model (Figure 3), an approach which I describe in detail in the main text (see also Roberts et al. 2014). I show key findings for each topic area, including the number of resolutions, number of references, topical alignment, topical proportion of the overall corpus, and age in Table 1 and illustrated in Figures 3, 4, and 5. The strategies used to measure alignment, resolution and reference count, and topic proportion are described in the main text, and the strategy for measuring topic age is described below.

### Temporal Effects

Across all topics, while the number of resolutions and topic proportions are relatively constant, the rate of referencing is increasing over time and varies across topic areas (Figure 5). On some topics, trends in reference rates and resolution rates move together ("south_africa"), but sometimes they exhibit distinct patterns ("unraw_administration," "conservation").

Figure 1: References increasing over time, but at a different rate than resolutions

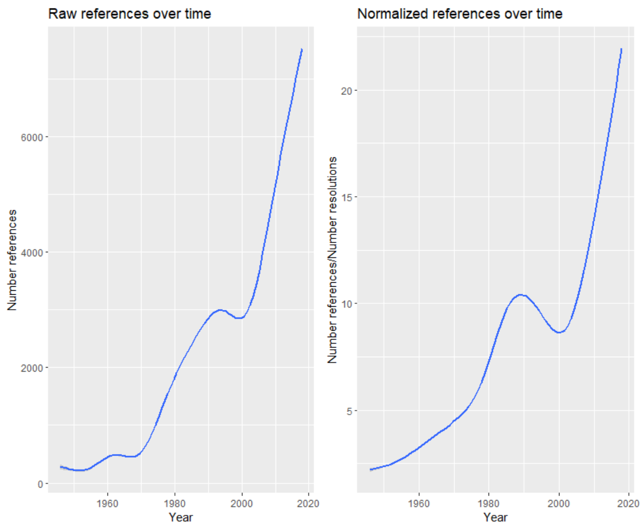



Figure 2: References increasing over time in both chambers, but particularly in the UNGA

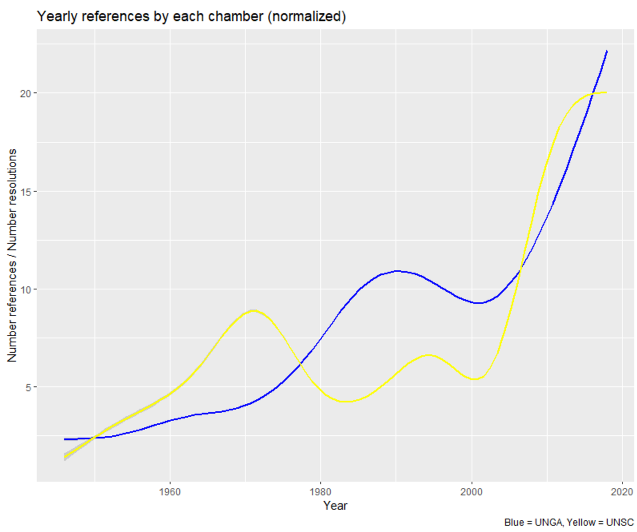
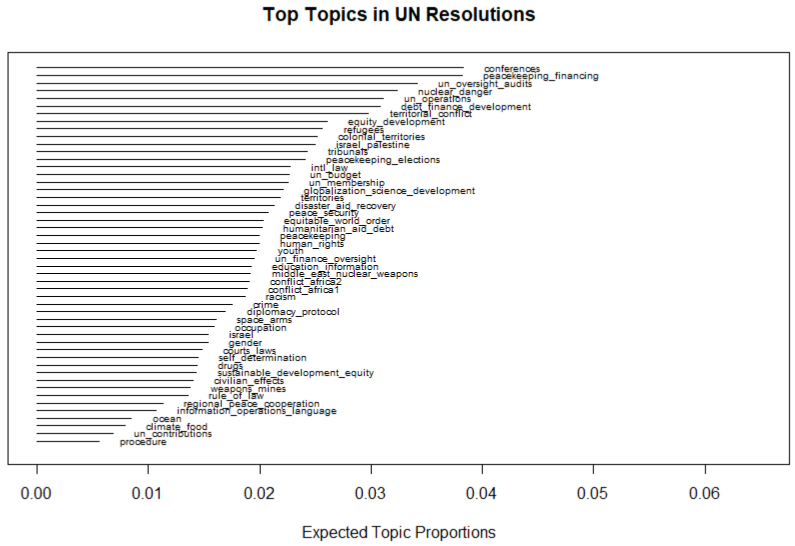


Table 1: Key findings by topic

| | Number Resolutions | Number References | Alignment (97.5 Percentile) | Topic Proportion | Age |
|---|---|---|---|---|---|
| peacekeeping | 344 | 2911 | 37.87 | 0.020 | 1949 |
| conflict_africa1 | 318 | 3853 | 40.78 | 0.019 | 1946 |
| peace_security | 352 | 4719 | 42.06 | 0.021 | 1946 |
| un_oversight_audits | 635 | 6488 | 28.53 | 0.034 | 1946 |
| tribunals | 398 | 1435 | 41.02 | 0.024 | 1946 |
| territorial_conflict | 459 | 2775 | 51.83 | 0.030 | 1947 |
| conflict_africa2 | 344 | 3385 | 44.67 | 0.019 | 1946 |
| peacekeeping_elections | 281 | 2468 | 36.56 | 0.024 | 1948 |
| civilian_effects | 232 | 1767 | 207.38 | 0.014 | 1946 |
| diplomacy_protocol | 295 | 1656 | 94.35 | 0.017 | 1946 |
| occupation | 286 | 2822 | 41.18 | 0.016 | 1951 |
| colonial_territories | 495 | 2586 | 187.75 | 0.025 | 1946 |
| information_operations_language | 157 | 1030 | 31.96 | 0.011 | 1946 |
| peacekeeping_financing | 671 | 12439 | 675.11 | 0.038 | 1946 |
| israel_palestine | 424 | 4268 | 98.29 | 0.025 | 1947 |
| courts_laws | 188 | 843 | 34.95 | 0.015 | 1946 |
| israel | 277 | 3273 | 79.10 | 0.015 | 1946 |
| drugs | 275 | 2657 | 72.94 | 0.014 | 1947 |
| gender | 278 | 2039 | 51.85 | 0.015 | 1946 |
| un_operations | 202 | 1158 | 25.41 | 0.031 | 1946 |
| weapons_mines | 251 | 1361 | 65.75 | 0.014 | 1946 |
| humanitarian_aid_debt | 372 | 2410 | 59.29 | 0.020 | 1946 |
| human_rights | 389 | 3289 | 61.73 | 0.020 | 1947 |
| refugees | 482 | 2252 | 35.94 | 0.026 | 1946 |
| ocean | 169 | 1334 | 43.50 | 0.008 | 1948 |
| education_information | 292 | 2189 | 34.23 | 0.019 | 1946 |
| space_arms | 279 | 2335 | 151.08 | 0.016 | 1958 |
| nuclear_danger | 589 | 5662 | 111.36 | 0.032 | 1948 |
| un_membership | 204 | 451 | 44.59 | 0.023 | 1946 |
| disaster_aid_recovery | 420 | 2741 | 54.82 | 0.021 | 1946 |
| self_determination | 269 | 1651 | 170.94 | 0.014 | 1949 |
| middle_east_nuclear_weapons | 355 | 4442 | 152.07 | 0.019 | 1947 |
| un_finance_oversight | 373 | 2519 | 62.44 | 0.019 | 1946 |
| equitable_world_order | 387 | 1923 | 46.51 | 0.020 | 1947 |
| crime | 330 | 2645 | 46.27 | 0.018 | 1946 |
| equity_development | 247 | 1551 | 32.53 | 0.026 | 1946 |
| conferences | 561 | 3872 | 34.24 | 0.038 | 1946 |
| sustainable_development_equity | 208 | 1553 | 249.83 | 0.014 | 1954 |
| rule_of_law | 212 | 2668 | 47.91 | 0.014 | 1950 |
| youth | 378 | 2370 | 42.03 | 0.020 | 1946 |
| debt_finance_development | 633 | 3520 | 58.56 | 0.031 | 1946 |
| globalization_science_development | 391 | 2978 | 52.80 | 0.022 | 1947 |
| un_budget | 435 | 2881 | 112.93 | 0.023 | 1946 |
| territories | 393 | 1881 | 198.30 | 0.022 | 1946 |
| regional_peace_cooperation | 223 | 1303 | 45.78 | 0.011 | 1948 |
| climate_food | 119 | 1346 | 74.46 | 0.008 | 1948 |
| un_contributions | 99 | 584 | 99.98 | 0.007 | 1946 |
| intl_law | 368 | 2415 | 48.90 | 0.023 | 1946 |
| racism | 362 | 2144 | 49.11 | 0.019 | 1946 |
| procedure | 26 | 39 | 31.32 | 0.006 | 1950 |

*Note:* Topic labels shortened for presentational purposes in the main text (Figure 4).

Figure 3: Resolutions by topic areas




Note: Estimation with Structural Topic Model (STM)

Figure 4: References and Resolutions by topic areas

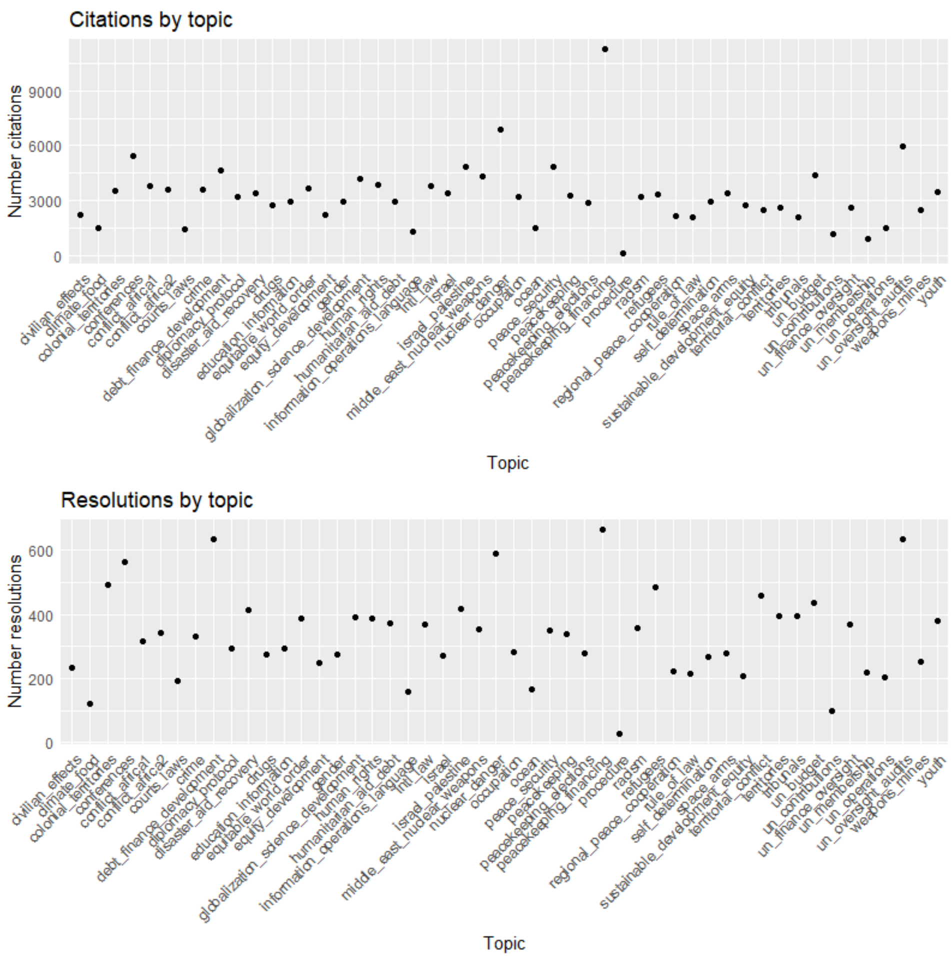
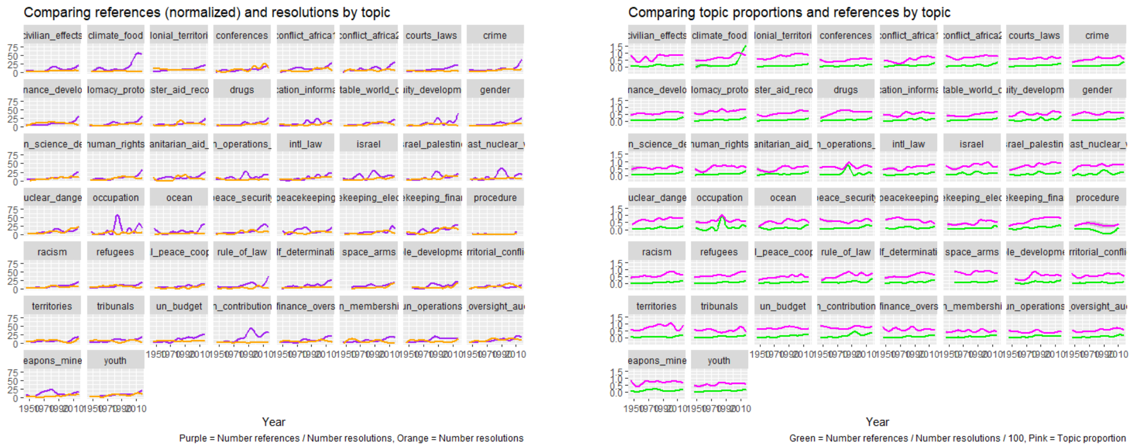


Figure 5: References and Resolutions by topic areas, over time (left); References and Topic Proportions by topic areas, over time (right)




Once issues are introduced onto the UN's agenda, they are unlikely to be removed because of bureaucratic inertia and state incentives to maintain institutional attention. (Hurd 2008, 114-118). I therefore measure topic age using the year in which a resolution with a given modal topic was first introduced onto the UN's working agenda. The data attest to the validity of this approach, showing that once a topic is introduced, the number of resolutions addressing it remains fairly consistent year on year (Figure 6). For most topics, the proportion of resolutions with that modal topic is also relatively flat over time, though some important exceptions where topic proportion notably changes over time—such as "conservation"—are present. The only topic that vanishes entirely from the agenda is "south_africa."

The age of most topics is essentially equal. 46 of the 50 topics I identify were first introduced during the first decade of the UN's work, which I can see in Figure 6. Alternative measures of issue age, including the mean of the resolution years for each topic, yield similarly little variation. Average resolution age is one such example—for 43 of the 50 topics, the average resolution age is 1990 or more recent, and average resolution age has a standard deviation of just 7.78. This finding suggests that the topics identified by the model may be too broad to capture temporal variation in issue introduction. As I discuss below, subcomponents of the various topics may be introduced at various points in time, but the larger themes I identify have been present on the UN's agenda in one form or another since the institution's founding.

# 3 Patterns in Referencing

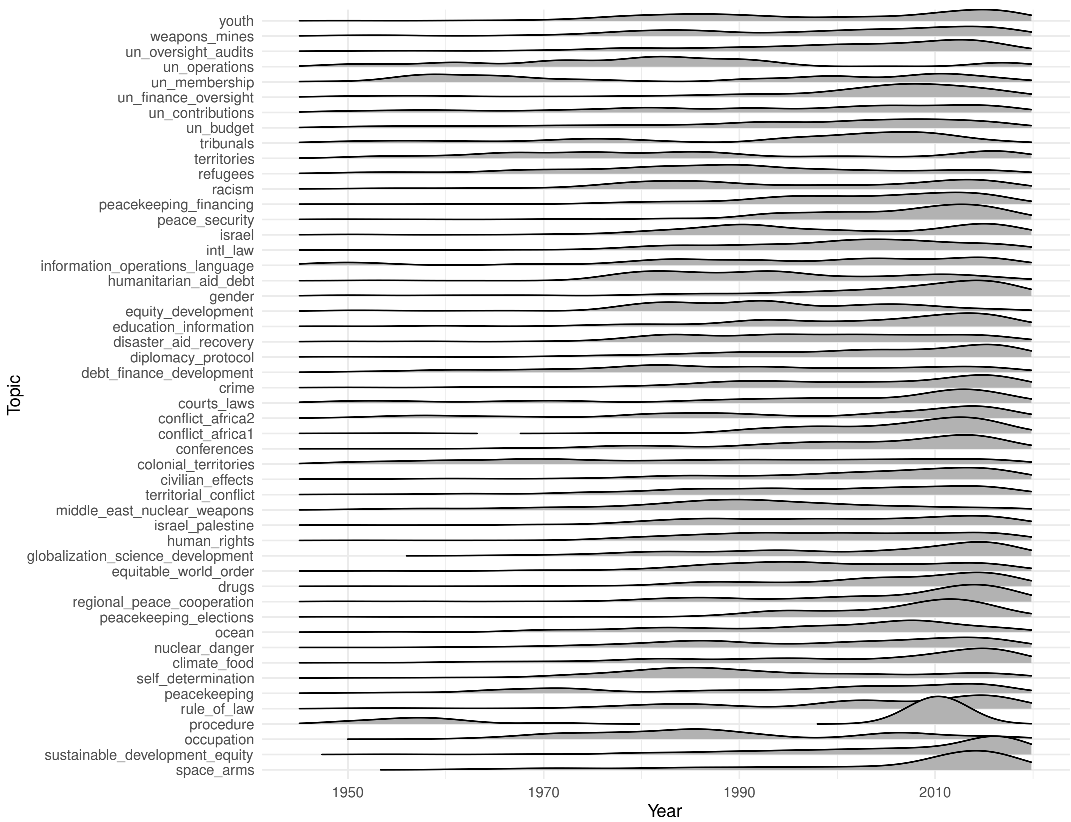
# 4 Political Effects

## 4.1 Sponsorship

Why do countries sponsor resolutions? Sponsoring resolutions in the UN can be costly, as sponsoring obliges a country to participate in drafting and negotiation sessions, to contract and consult with topical experts, and to expend social capital to cultivate support for the resolution amongst the membership. All of these actions are much more involved forms of cooperation than simply voting in favor of the resolution (Finke 2021). Therefore, countries are only likely to *selectively* sponsor resolutions, and as a costlier form of behavior, sponsorship can be considered a stronger signal of political support than voting.

Yet countries have an incentive to sponsor some non-zero number of resolutions in a given year to signal that they are contributing positively to the mission of the UN, which is an important factor for achieving elected leadership positions. Indeed, across the dataset, the average

Figure 6: Resolutions over time, oldest to newest topics




country sponsors 20% of the resolutions in a given year, which suggests that countries are indeed selective with their sponsorship choices.[1] Sponsoring a resolution more clearly attributes credit to a country for these purposes, and allows it to use the resolution for signaling or propaganda with domestic audiences. Soliciting more co-sponsors also serves strategic purposes, as it can signal wider agreement among the membership, which may pressure even non-sponsors to 'follow the herd' and vote in favor of the resolution (Mower Jr. 1962; Rai 1977).[2] I expect countries to sponsor resolutions only selectively because of the costs involved in sponsorship, as I previously discussed. Because of this potential costliness, sponsorship can be considered a strong test of my expectations. In the case of resolution sponsorship, I observe less systematic work on the determinants of sponsorship behavior.[3]. These analyses provide valuable insight into the patterns of sponsorship, but not into questions of the strategic decision-calculus of sponsorship. What makes a state more or less likely to sponsor a resolution?

The analysis of the relationship between referencing and sponsorship largely follows the strategy I outline in the main paper to assess the relationship between referencing and voting. To investigate the relationship between sponsorship and references, I first identify state sponsors for all resolutions for which sponsorship data are available through the UNGA Digital Library, which includes essentially all resolutions passed from 2000 onwards. In particular, for each resolution, I identify whether each country was listed as a sponsor of that resolution prior to that resolution's passage. To study relationships between sponsorship and references, I then calculate the following statistic, which is analagous to the statistic examining voting in the main

[1] Sponsorship data are obtained through the UNGA Digital Library and cover the period from 2000 onwards.

[2] Mower Jr. (1962) also describes a process of 'indirect sponsorship', in which a state works through a proxy to table a resolution. Analytically, this type of sponsorship cannot be empirically identified.

[3] But see Jacobsen (1969); Rai (1977); Smith (2006); Dijkhuizen and Onderco (2019); Finke (2021).

text:

$$S_t = \frac{1}{n_t}\sum_{i}^{n_t} \frac{N_{(i,t)}(sponsor, reference)}{N_{(i,t)}(sponsor)} - \frac{N_{(i,t)}(\sim sponsor, reference)}{N_{(i,t)}(\sim sponsor)} \tag{1}$$

Where $n_t$ is the number of countries in year $t$, and $N_{(i,t)}(sponsor, reference)$ is the number of resolutions sponsored by country $i$ in year $t$ that also reference resolutions that country previously sponsored at least once. $S_t$ therefore represents the average difference in a country's referencing rate for resolutions that country sponsors versus those it does not, which I average across countries and years. For example, suppose that the UN passes 100 resolutions in year $t$, of which 18 refer to resolutions sponsored by country $i$ and 82 do not. If $i$ sponsors 12 out of 18 resolutions that refer to $i$ and 38 out of 82 resolutions that do not refer to it, $S_{i,t} = \frac{N_{(i,t)}(sponsor,reference)}{N_{(i,t)}(sponsor)} - \frac{N_{(i,t)}(\sim sponsor,reference)}{N_{(i,t)}(\sim sponsor)} = \frac{12}{18} - \frac{38}{82} \approx 0.20$. As shown in Figure 7 (left panel), I find support for my hypothesis: resolutions that are sponsored by a country are approximately 50-75 percentage points more likely to refer to a resolution that country previously sponsored, compared with resolutions that country did not previously sponsor.

I conduct a similar exercise to compare sponsorship patterns based on defensive ally referencing and sponsorship patterns. I focus on military alliances specifically, which, as a form of 'deep' agreement are likely to be a stronger relationship between states than trade or other types of shallow agreements. Previous findings support this decision. Joining together in the relatively shallow BRICS alliance, for example, did not increase co-sponsorship behavior between members (Dijkhuizen and Onderco 2019), while membership in the EU, an extremely deep alliance, led to coordinate co-sponsorship behavior on human rights resolutions (Smith 2006, 127). To examine ally referencing and sponsorship patterns, I specifically calculate:

$$A_t = \frac{1}{|S_{(i,t)}|}\sum_{j \in S_{(i,t)}} (ally\%)_{(i,j)}$$

Where $S_{(i,t)}$ is the set of resolutions sponsored by country $i$ in year $t$, and $(ally\%)_{(i,j)}$ is the proportion of country $i$'s allies that sponsored at least one resolution cited in resolution $j$. $A_{(i,t)}$ represents the average proportion of country $i$'s allies that sponsored at least one resolution referenced in resolutions sponsored by country $i$ in year $t$. I also calculate this statistic for non-sponsored resolutions, and compare the two in Figure 7 (right panel).

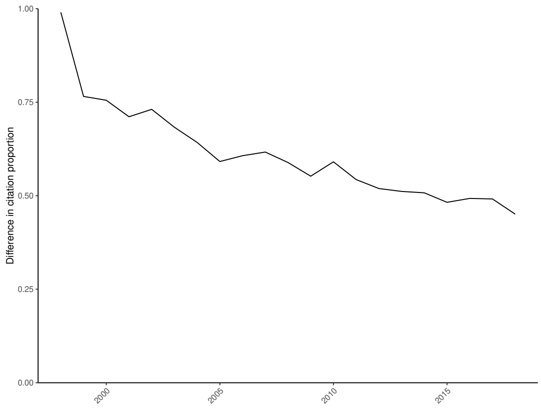
The results of this comparison also support my theoretical expectations. I find that the average proportion of a country's allies referenced in resolutions sponsored by that country is approximately 10 percentage points higher than the average proportion of allies referenced in resolutions not sponsored by that country. Since I only observe sponsorship and referencing decisions at the end of the negotiation process, I cannot be sure of the causal direction between referencing and sponsorship—that is, whether referencing is a strategy to induce sponsorship, or whether sponsorship leads to the inclusion of references. However, since sponsorship decisions usually come at the *end* of the negotiation process, this result suggests that referencing patterns have some persuasive impact on downstream resolution sponsorship decisions.

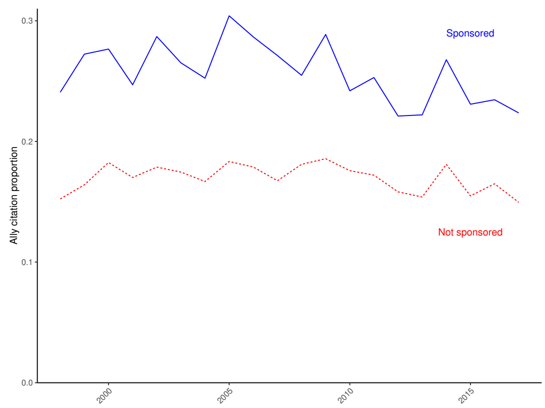
## 4.2 Voting

As I discuss and show in the main text, the inclusion of references to a resolution previously sponsored by a country increases the subsequent likelihood that it votes in favor of the resolution. I also find that this relationship holds for the inclusion of resolutions previously sponsored by one of the country's allies (see above).

I conduct several additional tests for the robustness of the key findings. One possible concern with the in-text relationship between references and votes among highly-aligned resolution pairs is that this relationship may depend on the number of total references in the resolution pairs. Resolutions with many references, in other words, may derive diminishing marginal political returns from additional references. To partially address this concern, I replicate the in-text results while controlling for the total number of resolutions in the older resolution in each pair

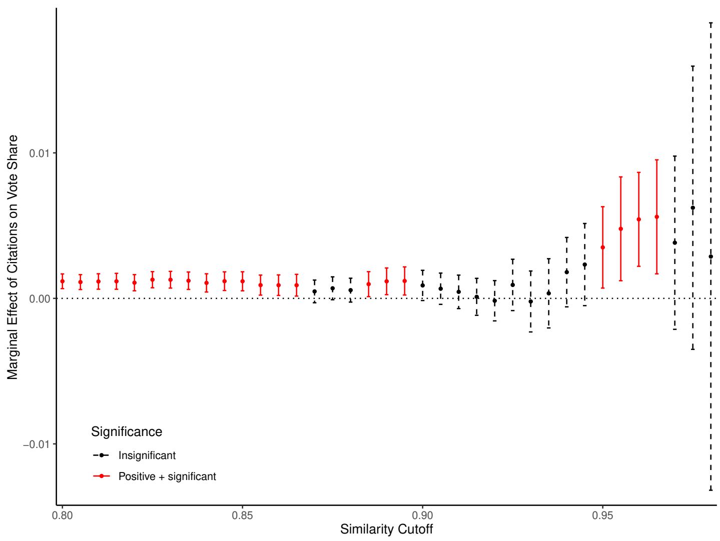
Figure 7: Difference in reference proportion, sponsored vs non-sponsored resolutions (left); Ally reference proportion, self-sponsored vs non-sponsored resolutions (right)



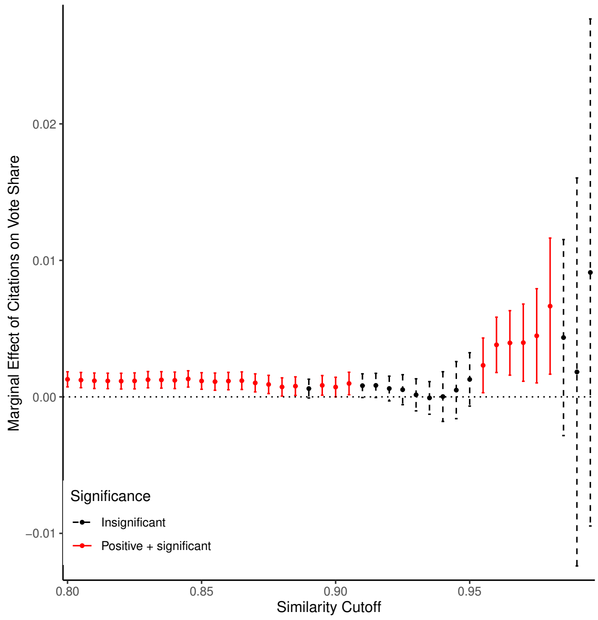

Note: Difference in voting proportions among resolutions where the state is referenced vs. not-referenced (left panel) and differences in ally voting proportions, among resolutions that the state votes for ('supported') vs. does not vote for ('non-supported') (right panel)

Figure 8: Relationship between votes and references for highly-aligned resolutions is robust, controlling for the total number of references



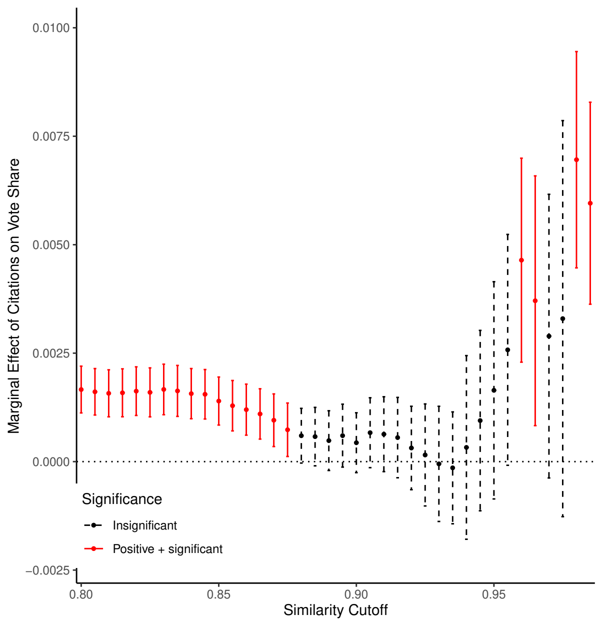

Note: OLS linear regression model. The dependent variable is the difference in proportion of yes votes between pairs of highly-aligned resolutions. The key predictor variable is the difference in the number of references for each resolution. Each point represents a model fit with all pairs with similarity scores above a given cutoff. Fixed effects are included for the year of each resolution in the pair.

Figure 9: Relationship between votes and references for highly-aligned resolutions is robust with dyad-robust clustered SEs



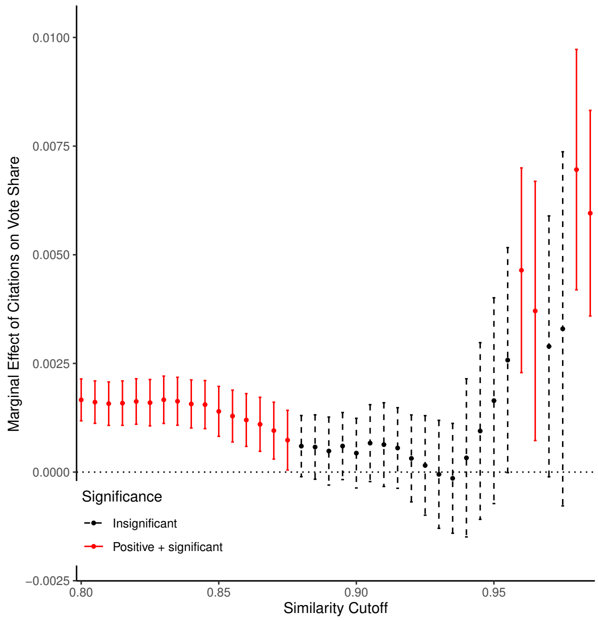

Note: OLS linear regression model. The dependent variable is the difference in proportion of yes votes between pairs of highly-aligned resolutions. The key predictor variable is the difference in the number of references for each resolution. Each point represents a model fit with all pairs with similarity scores above a given cutoff. Fixed effects are included for the year of each resolution in the pair.

Figure 10: Relationship between votes and references for highly-aligned resolutions is robust with year-pair fixed effects




Note: OLS linear regression model. The dependent variable is the difference in proportion of yes votes between pairs of highly-aligned resolutions. The key predictor variable is the difference in the number of references for each resolution. Each point represents a model fit with all pairs with similarity scores above a given cutoff. Fixed effects are included for the year-pair.

Figure 11: Relationship between votes and references for highly-aligned resolutions is robust when cases of no changes in no votes are omitted




Note: OLS linear regression model. The dependent variable is the difference in proportion of yes votes between pairs of highly-aligned resolutions. The key predictor variable is the difference in the number of references for each resolution. Each point represents a model fit with all pairs with similarity scores above a given cutoff. Fixed effects are included for the year of each resolution in the pair.

(Figure 8). I find that the results are essentially unchanged. Importantly, this finding does not preclude the possibility of diminishing marginal returns from referencing patterns. Among the set of highly-aligned pairs of resolutions, total reference counts are relatively uniform. For example, among the set of resolution pairs with a similarity score of 0.8 or higher, some 80% of pairs have 15 or fewer references in the older document, compared with an overall in this set of 107 references. As such, diminishing political returns to referencing may be present in resolutions with a particularly large number of references, but the data contain insufficient observations in this region to identify or rule out this pattern.

In addition, I show in Figure 9 that results are robust when the estimated standard errors are replaced with dyad-robust clustered standard errors, drawing on the insights of Aronow, Samii, and Assenova (2015), as well as when year-pair fixed effects are included. Finally, one may be concerned that the results are being driven by cases of states changing from absent or abstain to yes votes, rather than true vote switching from no to yes. I discuss in the main text the political importance of absenteeism and abstentions, nevertheless, I show that the results are not being driven by such cases. I omit dyads in which there is no change in no-vote proportion and recover the main results, although with greater uncertainty (Figure 12).

### 4.3 US Aid

In addition to the main analysis comparing US aid to references, which is aggregated at the year-level following the approach employed by Dreher, Nunnenkamp, and Thiele (2008), I also analyze these relationships at the resolution level following Carter and Stone (2015). In this analysis, I specify the model:[4]

[4] I thank an anonymous reviewer for this suggestion.

$$Vote_{irt} = \beta_1 Cite_{irt} + \beta_2 US_{rt} + \beta_3 US_{rt} \times Aid_{it} \tag{2}$$

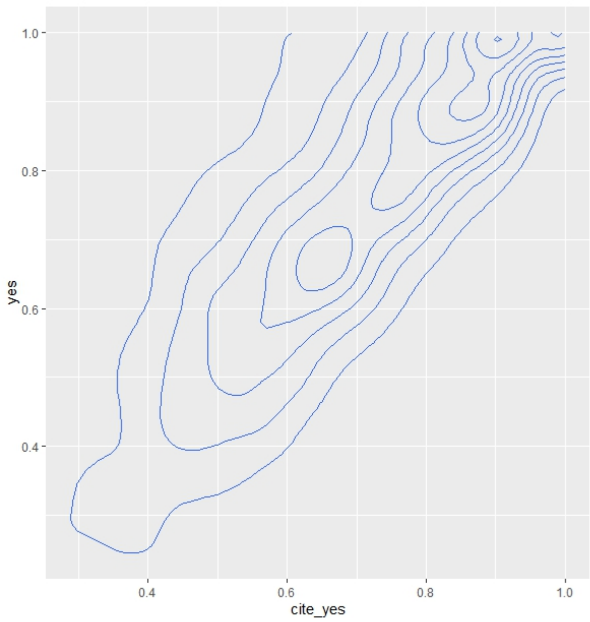
in which Vote represents whether country $i$ votes yes on resolution $r$ in year $t$. Ou remain predictor of interest, Cite, reflects whether the resolution references another resolution (from any prior year) on which country $i$ voted yes. US captures how the US voted on the resolution, and Aid captures US aid to country $i$. I estimate an OLS model with country and year fixed effects. I recover my main finding at the resolution level: referencing is a significant, large positive predictor of voting. Strikingly, in this model, US aid becomes insignificant as a predictor of voting.

Table 2: Predicting Votes at the Resolution Level

| Model: | (1) |
|---|---|
| *Variables* | |
| References | 0.668*** |
| | (0.013) |
| US Votes Yes | -0.008 |
| | (0.008) |
| Aid | $1.35 \times 10^{-5}$ |
| | $(1.31 \times 10^{-5})$ |
| US Votes Yes × Aid | $-4.38 \times 10^{-5}$ |
| | $(3.08 \times 10^{-5})$ |
| *Fixed-effects* | |
| Country | Yes |
| Year | Yes |
| *Fit statistics* | |
| Observations | 2,139,587 |
| $R^2$ | 0.617 |

*Clustered (Country) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 12: Joint distribution of aid and references

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