Patterns of Global Politics

Geopolitical Entity Networks in the UN General Assembly

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Conceptualizing and measuring state influence in international relations is inherently difficult. In this paper, we propose a new, relational measure of state importance within the international system. We argue that asymmetrical distributions of attention among states reflect their centrality, and thus approximate their influence in the international network. Specifically, we utilize the UN General Debates and named entity recognition (NER) to identify which states mention each other in their speeches, build annual directed networks of mentions, and extract measures of centrality for each state based on these networks. We show that this relational approach to influence descriptively highlights expected trends of state importance and is driven in particular by indicators explaining state influence as a function of state size. Finally, we argue that this approach can be generalized to other arenas of international politics, or even different political arenas entirely, to gauge actor influence within the networks of those arenas.

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Introduction

In their annual speech of the United Nations General Debates in 2019, the Eritrean delegation, represented by Mr. Osman Saleh Mohammed, proclaimed that

> [a]ll vital parameters indicate that the unipolar world order has come to an end or is in its twilight years. (Mohammed, 2019)

This statement represents an example of a longstanding discussion in the international relations literature. What are the true structures and dynamics of the international system? This debate has grappled with both what type of international system we are currently living in (Zhao, 2021; Mearsheimer, 2021; Røren, 2024) and how to define the past (Walt, 2008; Wagner, 1993; Saperstein, 1991). While understanding global patterns of politics is an important endeavor, observing international politics systematically is difficult without narrow scopes and limited time frames. Yet, one way of observing all the states of the world both at once and over time is to analyze the one institutional arena where they all meet: the United Nations General Assembly (UNGA) and its annual General Debates (UNGD). The main contribution of this paper is to propose a new, relational measure of state influence within the international system based on member state attention in the institutional setting of the UNGA generally, and the UNGD more specifically.

Since its first session on January 10th 1946, the UNGA has been the main arena for deliberation between UN member states. The UNGD is the only UN body with universal membership, equal access to participation for all members, and the only body that persists throughout the period. In general terms, the UNGA can be seen as an institutional expression of an *international society* (Bull, 1977; Peterson, 1992; Buzan, 1993): a group of states that "conceive themselves to be bound by a common set of rules in their relations with one another, and share in the working of common institutions" (Bull, 1977, p. 13). Crucially though, as all international organizations, the UN is a "pseudo-institution" because its effect ultimately relies on the long-term practices of its member states and can become entirely ineffectual in practice if not supported by the norms and behaviors of international society. As such, we find the term *international network* useful in approaching the distribution of influence in the UNGA. Approaching it as a *network* is especially fruitful because it does not evoke assumptions about any particular power structures, anarchic dynamics or dominant nodes. Moreover, the UNGD is a theoretically suitable institution to study this network in because it is shaped both by its own rules and regulations, the characteristics of its members, and the properties of the international network. Empirically, the UNGD also provides, through its written records, a rich source of information about these practices. Given the platform the UNGA provides, the statements and expressions states make here should serve as important, though complex, signals about what – and whom – the states care about.

In this paper, we leverage the UNGA setting to propose an new approach for measuring influence in inter-state relations on the global scene. By assuming that the UNGA is an international network of states, we can use speeches from the UNGD to map patterns of attention between member states, and thereby approximate states' influence in the international network through their *centrality*. Given that attention is a finite resource in the UNGA, we assume that being the center of attention picks up on a state's ability to influence the other states of the network, thereby representing relative importance between states. In essence, this approach is closely related to the way we use citations in academic work to measure the influence of authors, and how legal arguments invoke citations of previous judicial decisions that have bearing on the case at hand. Applying this perspective empirically, we arrive at both a new proposed general approach to observing global politics, and an attempt at elucidating the comparative empirical strength of various IR theories when put to the test using our measurement approach.

Specifically, our empirical design utilizes named entity recognition (NER) on over $10,000$ speeches (1946-2022) from the United Nations General Debates Corpus (UNGDC), readily available from Baturo et al. (2017) and Jankin et al. (2024), to map attention between member states. These entity mentions are then used to construct annual networks of interactions – where member states are connected if they mention each other – from which we utilize established network centrality measures to assign centrality scores for individual member states. Ultimately, we build a country-year dataset of centrality scores, which is easily appended with other country-specific data sources. In extension, we showcase how these measures of influence descriptively reflect expected temporal trends in international relations, for example through the US being a dominant player throughout the period, the rise and fall of Russia before and after the Soviet Union, and the continuous decrease in the influence of Great Britain.

In our main analysis, we test our measure against three types of influence drivers commonly used to assess influence in IR research. Here, we find that our measure inhibits strong aspects of *strength through size* indicators (GDP, population, and national capabilities), only partial impact from *spheres of influence* indicators (trade flows, ideology, and regime type), and that it is responsive to current focal point indicators (regime breakdown, national emergencies, and security council membership). Further refining our results, we also estimate centrality measures for influence driven by positively charged and negatively charged attention networks using sentiment analysis. The *strength through size* indicators remain strong drivers in both of these subcategories, with the size of a state's economy being a particularly strong driver of influence across all our modelling specifications. When separating between positive and negative attention, we also find that more democratic states receive less negative attention than others, but this finding is less robust to alternative modelling specifications.

Of course, it remains a central question whether our observations and inferences in the UNGA can travel to outside the institution itself and say something more general about the distribution of influence in the international network. Though we draw on general IR scholarship to deduce theoretically interesting perspectives about the characteristics of international society, what we examine in practice is only the expressions these take within the scope of the UNGA. Yet, given the importance of the UN as an arena for international conversations, we find it the most suitable institution available for drawing such inferences. Moreover, we argue that our general empirical approach is highly flexible and transferable to many other institutional settings. By extracting the actors in any arena (e.g. UN committees, international and regional organizations, national legislatures) with NER and building networks of influence based on the attention they give each other, one can infer how influence, following our used definition of the term, is distributed across a range of other networks.

In the following section, we detail the UNGD as an institutional arena before we lay out our theoretical underpinnings for the connection between influence, importance, and centrality in the international network. Next, we discuss the expected drivers of influence through the *strength through size* and *spheres of influence* approaches from IR scholarship. We proceed by describing the data and methodology used to construct our measure of influence, before showing descriptive trends and analyzing drivers of centrality. Finally, we discuss the implications of our approach and discuss its generalizability beyond the UNGA setting.

United Nations General Debates

Hosted at the UN headquarters in New York, the United Nations General Debates (UNGD) has been held annually since 1946 at the start of the General Assembly sessions in late September. The debates usually last for about two weeks in total. All UN member states (and some non-member states) are invited to share their views on issues and developments in the world at the debates. The speeches can focus on whatever the speaker wants, but the President has, since 2003, suggested an issue or thematic focus for the debates (United Nations, 2021).

The debates themselves are guided by the *Rules of Procedure of the General Assembly* (United Nations, 2022). Here, although no formal limits are set, speakers are encouraged to not be "excessively long" (United Nations, 2022, p. 69) and speak for about thirty-five minutes. The order of speakers is decided by preparing a Speakers' list where member states, through their delegations, place themselves on the list in a preferred time slot. If their preferred slot is taken, the Rules of Procedure encourage delegations to ask for time slot exchange. There are, however, also some informal norms, as with other UN institutions (see Wiseman (2015)), guiding the order assignment: the UN Secretary-General first reports on the current work of the UN before the President of the General Assembly takes the floor to make an opening statement. Further, Brazil has been the first member country to speak since 1955. This is attributed to Brazil being the only country with a willingness to be first out in the earlier UNGDs, which then turned into a norm or tradition. Next, the United States is usually the second state to take the podium because they are the host of the debates (Capel, 2019). This amounts to one of the great benefits of using UNGD empirically to map how states position themselves and maneuver the international system; all member states are equal and have the same opportunity to participate under the same rules.

In approaching this empirical mapping of international order and relations through the UN General Debates, we make some important assumptions. Most importantly, we assume UNGD speeches to be well-crafted and to represent the product of significant deliberation in UNGA member states' foreign ministries (see Baturo and Gray (2024) and Kentikelenis and Seabrooke (2017) for discussions). As such, we assume that it is possible to draw inferences about a state's position in the international system and relationship with one another from how they refer to each other during the General Debates. Of course, the crafted nature of this speech also means that the true objectives and purposes of states can be obfuscated and diluted. States speak with a number of intentions: to strengthen alliances, to address adversaries, to name and shame norm violators, and sometimes to just uphold formal expectations. Consequently, we are careful to interpret our findings primarily as states giving and receiving *attention* rather than inferring the normative connotations of that attention.

Influence, importance and centrality in the international network

Because the concept of *power* has long traditions of being operationalized and measured through indicators of material capability (Waltz, 1979), our conceptual focus rather revolves around state *influence* to better capture the relational character of our approach. These concepts are, however, tightly connected at an overarching level. For instance, as noted by Singer (1963), power can be defined as the "capacity to influence" in international politics. Moreover, he notes that

> the concept does not come to life except as it is observed in action, and that action can be found only when national power is brought into play by nations engaged in the process of influencing one another (Singer, 1963, p. 420).

To Singer, influence is the capability of one state to alter the choices or preferences of other states. To truly observe influence, we must know the counterfactual actions of states: if state A intends to do Z and state B convinces state A to rather choose to do Y, we know that influence has occurred. But, observing true intentions (Z) is inherently difficult. Relatedly, Knoke (1990) argues that *influence* is a relational sub-component of power because it necessitates communication between actors. In the case of the UNGA, this would entail that member states transmit messages through their speeches and that the audience (other member states) "receive, decode, interpret, and react" (Knoke, 1990, p. 3) to the speech. Again, observing true influence is inherently hard. Therefore, we need more approximate approaches in order to observe influence.

In this paper, we suggest a relational approach to observing the influence of states: namely, by mapping their *centrality* in the international network as it appears in the UNGA. Regarding the international system as a network is largely intertwined with network analysis as a methodological approach (see Hafner-Burton et al. (2009) for an overview) which we will detail below. To lay out our theoretical understanding of network centrality as a proximate influence measure, we begin by defining the setting in which centrality occurs. Beyond specific institutions and international organizations, we can imagine all the states of the world as being part of an abstract, implicit global network.[1] Certainly, in the implicit network, some states have many more connections, with much longer reach, than others, and some states also dominate those connections to a much larger degree than their counterparts. Yet in the UNGA, the implicit network of states is explicit and even largely set and stable. Here, representatives from all states meet regularly, have speaking access, and voting rights, within a formal frame. We find the term *network* especially fruitful as a point of departure because it does not, in and of itself, evoke assumptions about any particular power structures, anarchic dynamics or dominant nodes. In the UNGA setting, then, we can put the characteristics of the network to the test.

Within this network, *centrality* is a characteristic of how many connections a state has, and how frequently those connections are active (Hafner-Burton et al., 2009). In other words, centrality is a measure of how much attention a state receives. Each observation of a connection is an observation of attention, which is always a limited resource across arenas. We argue that this serves as an approximation of influence because it captures the opportunities a state has to exert influence. At the very least, we are able to capture variation in the *importance* of each state as compared to its peers. And, even if we do not observe the change in behavior that influence implies in its full form, we do capture the varying extents to which states appeal to one another in the network. Hence, though influence and centrality are not analogous terms, we argue that it is likely that they are closely linked.

We think of network centrality as a feature that can capture the essence of influence in the international network, both at the level of the system as a whole (*network centralization*) and at the level of the state (*network centrality*). Yet, the particular institutional setting in which it is observed will of course shape the assumptions we make about its particular attributes. In the UNGA specifically, there are therefore some key characteristics that are important to keep in mind when thinking about what centrality in this specific network can and cannot capture. First, as all UN member states have equal access to addressing the UNGA during the General Debates, *attention* is not only a finite resource in the general sense of the term, but also a formally finite resource. In addition, assuming speeches to be well-crafted, the prioritization involved in giving attention to a particular state should be well thought through: in

[1] See Kinne (2018) for a similar approach to the global network of bilateral agreements.

the UNGA setting, then, we can assume that centrality, as an aggregate of attention between network connections, picks up on very intentional state behavior.

Existing explanations of influence in the international network

Defining the characteristics of the international system has been a key pursuit for scholars of international relations since the discipline's inception (Rosecrance, 1966; Chase-Dunn, 1979; Jervis, 1998). In the aftermath of World War II, the conceptualization and definition of the international system by scholars of international relations transformed with geopolitical shifts and the emergence of new global actors (Slaughter, 1997; Ruggie, 1992; Walt, 1998, Dicken (2003)). Traditionally rooted in realist and liberal frameworks, the post-Cold War era has witnessed a nuanced exploration of the international system that extended beyond conventional state-centric analyses (Pfaltzgraff, 1974). Scholars grappled with the complexities introduced by the bipolarity of the Cold War (Knutsen, 1997), as well as the growing interdependence among states in the realms of economics, security, and information (Nye, 1990).

From this literature, we will zero in on two overarching explanations of how the international system works. We focus on analyzing explanations that have a large scope, both in terms of geographical applicability, but also in terms of the time periods they cover. In short, we are interested in applying perspectives from the literature that point to "paradigms that can make powerful and parsimonious claims about conflict and cooperation in post-Cold War global politics" (Voeten, 2000). In his influential article, Voeten emphasizes a series of prominent examples of such paradigms: the divide between rich and poor countries, the North-South and East-West divides, clashes of civilizations, conflict between democracies and nondemocracies, and the power struggles between the hegemon (USA) and a counterhegemonic bloc. With this suggested list of explanatory paradigms in mind, we conceptualize *two major blocks* of explanations into which we sort the different features: the "Strength through size" explanations and the "Spheres of influence" explanations. The Strength explanations describe global politics as a matter of strong versus weak, while the Spheres explanations describe global politics as a system of alliances. Through probing the strength of these existing explanations using our centrality measurement approach, we both seek to test the comparative empirical strength of these explanations, and illustrate the usefulness of our measurement approach.

Spheres of influence: Alliances and Ideologies

Our first block of explanations consists of angles that point to the salience of alliances, broadly defined, in the international network. This block of explanations is closely related to the debate over the *poles* of international society (Jervis, 1991). The concept of "spheres of influence" is typically defined as geographic areas or regions where a particular state or states exert predominant influence, recognizing the territorial limits within which states seek to assert their political, economic, and military influence, navigating a balance between cooperation and competition. The delineation of spheres of influence has historical roots, notably during the 19th and early 20th centuries, when major powers partitioned the world into zones of control. In recent years, the concept persists as a lens through which analysts interpret the ebb and flow of international relations, reflecting the complexities inherent to the global geopolitical landscape. During the Cold War, there were predominantly two spheres of influence, also known as bipolarity (Jervis, 1991). Another potential underlying feature of the two spheres is the role of ideology. As argued e.g., by Voeten (2021), ideological contestation is an important feature of international institutions. Given that this can manifest through similarly minded states grouping together in the international network, we include ideology in the spheres of influence-group of explanations.

In practice, there are several ways of observing spheres of influence. One approach is to focus on the two poles of the Cold War era and track how USA and USSR dominated global politics until the end of the Cold War. Another is to look at the underlying characteristics that contribute to creating different spheres of influence beyond these two specific states. In addition to observing the influence of decisive superpowers over time, we will also look at the ways in which different alliance-relevant traits in themselves influence the international network. Specifically, we are interested in how a) democracy, b) trade flows, and c) ideology serve as drivers of states' centrality in the global network. Democracy is included to proximate shared values, while trade flows proximate connectivity.

Strength through size

Our second block of explanations address the basic aspect of strength through size. Are large states more central and influential in the international network than those less advantaged? In a nutshell, we are interested here in examining how a set of features of state *strength* drive a state's influence in the international network. While it is uncontroversial that smaller, less powerful and less economically advantaged states must to some extent gravitate towards the large powers of the world, there are enumerable ways of capturing the concept of power more broadly (Baldwin, 2016). We therefore focus here on strength through size rather than any larger, complete notion of the power concept. The size features we will focus on are a) the economy, b) population and c) military capabilities.

First of all, the role of income is in any case a non-negligible element to global power dynamics. In early research on voting patterns in the UNGA (see e.g. Russett (1966)), the division between rich and poor countries has in fact been found to be the most important dimension (Kim and Russett, 1996). To capture strength more fully, however, it might also be the case that large populations in and of themselves give states a prominent role in the international network. In addition, to approximate more closely a notion of power as a driver of influence, we also include the size of a state's military apparatus.

Finally, we should be able to observe clearly delineated temporal patterns. Specifically, we expect to be able to detect how the largely bipolar world of the post-WWII years, as captured by the "spheres of influence"-explanations, changes into a much more unipolar world in the post-Cold War years. In general, the motivations that drive states' tendencies to build certain alliances, speak to like-minded states, and seek legitimacy, should be far from static across the 1948-2022 time period we investigate here. Moreover, the possible temporal heterogeneity of the salience of economic power and "strength through size" explanations is also an interesting question in its own right, as well as whether both of these blocks of explanations follow the same general temporal patterns.

Overall then, we will investigate the explanatory power of both of these larger groups of explanations, both compared to each other, and across the temporal period covered in our data. Our two main theoretically driven questions are therefore: What state traits drive centrality and influence in the international network? And how should this have changed over the last 70 years? Through the accompanying analysis, we are also aiming to showcase what the centrality measure is capable of capturing, illustrating its usefulness also to analyses beyond ours.

Data and Methodology

For our task of measuring state influence at the international arena, we draw on all speeches in the UN General Debates from 1946 to 2022. In the following section, we describe this corpus and detail how we construct our measure of member state importance. Futher, we present descriptive summaries and trends of this measure. Finally, we describe the research design and independent variables used to analyze the drivers of centrality.

United Nations General Debates Corpus (UNGDC)

The UN General Debate Corpus (UNGDC) (Jankin et al., 2024; Baturo et al., 2017) is the foundation for our measurement construction and analyses. The UNGDC spans from 1946-2022 and includes all speeches in the annual UNGD meetings. The corpus contains over 10 000 speeches mapped to the individual holding the speech and their affiliated country. This is a very rich and unique data resource that has been used in explaining a variety of questions about the international arena (see Jankin et al. (2024) for an overview).

There are, however, also some drawbacks with our application on UNGDC. First, it is well-known within Natural Language Processing (NLP) that individual style, language, dialects, topic, and context are important for text generation (see e.g. Jin et al. (2022)). If we accept that different individuals will generate, at least slightly, different texts, this could be a limitation for relying on the assumption of member states as unitary actors, when our measure is based on individual representatives' text generation.

Second, the transcripts used here are the English translations of the speeches, which are originally held in in numerous different languages. Things might be lost in translation, but this measurement error is minimized by the fact that the speeches are translated by trained translators to a variety of languages and that we only rely on geopolitical entity extraction. As such, we assume equal meaning between the original and translated language.

Finally, we assume that the order of speeches is inconsequential for the content of the speech; if the order was scrambled, the same entities would be mentioned by member states. This might also be problematic because a speaker can reply to speeches already held, but not the other way around – once a member state has spoken, it will not get that opportunity again. As such, the later speakers can be more influenced in their entity mentions than the earlier speakers. We do, however, maintain that the craftedness of the speeches and effort that goes into writing them should limit this problem.

In sum, these limitations should be considered when applying our operationalization of influence in the international system and interpreting the results from the following analyses. Below, we describe how we extract named entities, build dyads, and estimate centrality measures for the network of mentions in the UNGD.

Named Entity Recognition

We obain named entities by parsing all speeches in the UNGDC through the `spaCy` Natural Language Processing kit (Honnibal et al., 2020) using the `spacyr` (Benoit and Matsuo, 2023) package for `R` (R Core Team, 2023). In short, The Named Entity Recognition (NER) parser is trained to identify objects of the world (entities) that have a specific name based on the structure and context of the input text. Of course, entities come in different types at different levels, such as buildings, countries, dates, and so on. For our purpose, we extract only the `GPE` (geopolitical entities), which includes countries, cities, counties, municipalities, and so on.[2] In the next step, we convert the `GPE` entities to three character ISO codes via the `countrycode` package for `R` (Arel-Bundock et al., 2018). This cleans up the non-country `GPE` automatically by assigning all entities without a matching ISO code as `NA`. In the time span from 1946 to 2022, there are, of course, some issues with countries splitting up, changing name, merging, etc, but we generally follow the principle of "largest heir" in order to keep the time series for each member state as long as possible (see Coppedge et al. (2024) for details). For example, it follows that the Soviet Union and Russia will be coded as the same country.

Finally, we construct a dataset of all possible dyads between speakers within UNGD sessions and how many times they have mentioned each other in that session. This is the foundation for the construction of the annual networks and subsequent measure of member state importance. In addition, as studies have shown that countries are highly adaptable in the language they use to describe other countries based on their ties (see e.g. Terman and Byun (2022)), we also run sentiment analysis to be able to

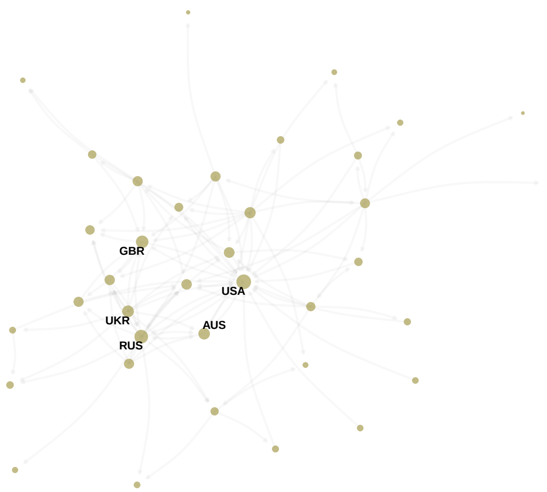
[2] We also extract the `NORP` (nationalities, religious, and political groups). But, our measure only utilize the `GPE` mentions, because `NORP` refer to quite different and more personalized types of entities than `GPE`.

distinguish between positively and negatively charged attention. This process is described further below.

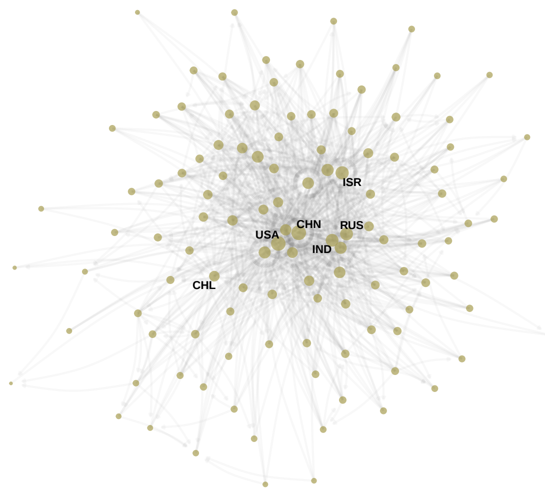
Networks of Mentions

Figure 1: Network of mentions in the UNGD for selected years. Nodes represent countries and links between the nodes form if one node mention (one time or more) another node in their speech. The edges are directed. The size of the nodes indicate the node's centrality in the network.

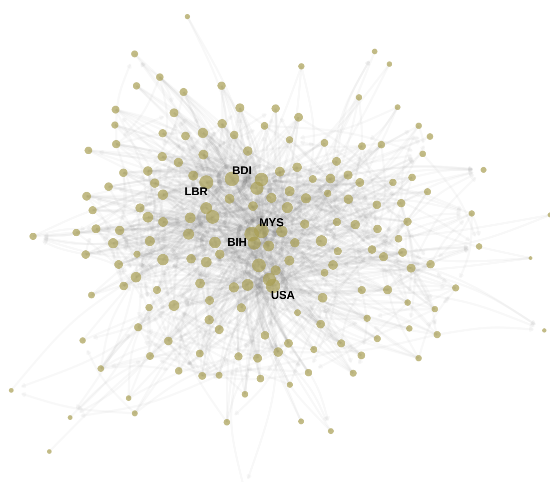
(a) 1946



(b) 1971



(c) 1996



We use the dyadic dataset to set up annual directed networks between member states participating in the UNGD though the `igraph` package (Csardi and Nepusz, 2006). More specifically, for each year of the UNGD, we make a network where countries are nodes and mentions are edges (links between nodes), as visualized for some selected years in Figure 1. In this figure, the size of the nodes are based on the eigenvector centrality (Bonacich, 1987) of that node and the five highest scoring countries are marked by labels in each panel in the figure. These scores also constitute our main measure of member state importance, as will be discussed in detail below. Although our main analysis is agnostic to the tone of mentions, we follow the same approach to estimate networks of positive and negative GPE mentions separately (see tables 2 and 3 in the Appendix).

Naturally, Figure 1a is a lot more sparse than the other panels as a consequence of there being fewer member states in 1946. Here, the three most central nodes in the network are the core of the allied countries during World War II – the USA, Russia, and Great Britain. Moving to Figure 1b, in the much larger assembly of 1971, the two protagonists of the Cold War – USA and Soviet Union (RUS) – manifest themselves as central nodes (also see Figure 3). However, the rising prominence of the Southeast Asian powerhouses – China and India – and Israel among the most central nodes in the 1971 network. The rise of China and India in these networks exemplifies how the annual scores can be sensitive to current focal points; China was in the middle of the Cultural Revolution and 1971 in particular saw heated discussions over replacing the Republic of China with the People's Republic of China in the UNGA (Pan, 2009). India was on the stairs of the Indo-Pakistani War of 1971. Israel and conflicts in the Middle East is, of course, also very salient issues by the 1970s, which generate a lot of attention in the UNGD.

However, after the collapse of the Soviet Union, Russia is no longer among the most central nodes in the network, as shown by Figure 1c, and the USA is the only member state consistently measured as an important state in the network. Further, we see a continuing pattern of salient conflicts within or between states leading to brief spells of importance for those states. For instance, Bosnia & Herzegovina (BIH), was the most central node in 1996 (Figure 1c) in the aftermath of the Bosnian War; a war where UN peacekeeping forces were heavily involved (Costalli, 2013).

Centrality Measure

There are a myriad of ways one can summarize information from networks and different measures might serve different purposes. Network centrality measures aim at prescribing scores of importance to nodes in the network based on their connection to other nodes in that network. This can be done by counting the edges (GPE mentions) going into a node (member state) from other nodes – usually referred to as *in-degree* – going out from a node to others (*out-degree*), or various combinations of the two (see Freeman (1978) for an overview). In our approach, we focus on eigenvector centrality (Bonacich, 1987) as a measure of member state importance in the UNGD. However, we also provide a range of other measures in our data (see Table A3-1 in the Appendix) and the underlying networks, for which one can estimate any network statistic. We do note that, as shown in Figure A3-3 in the Appendix, that *out-degree* is a lot more balanced between speeches than *in-degree*. This does indicate that the UNGD arena is, in fact, used quite similarly by different speakers in terms of how many GPEs they mention, and that *who* they mention varies more systematically.

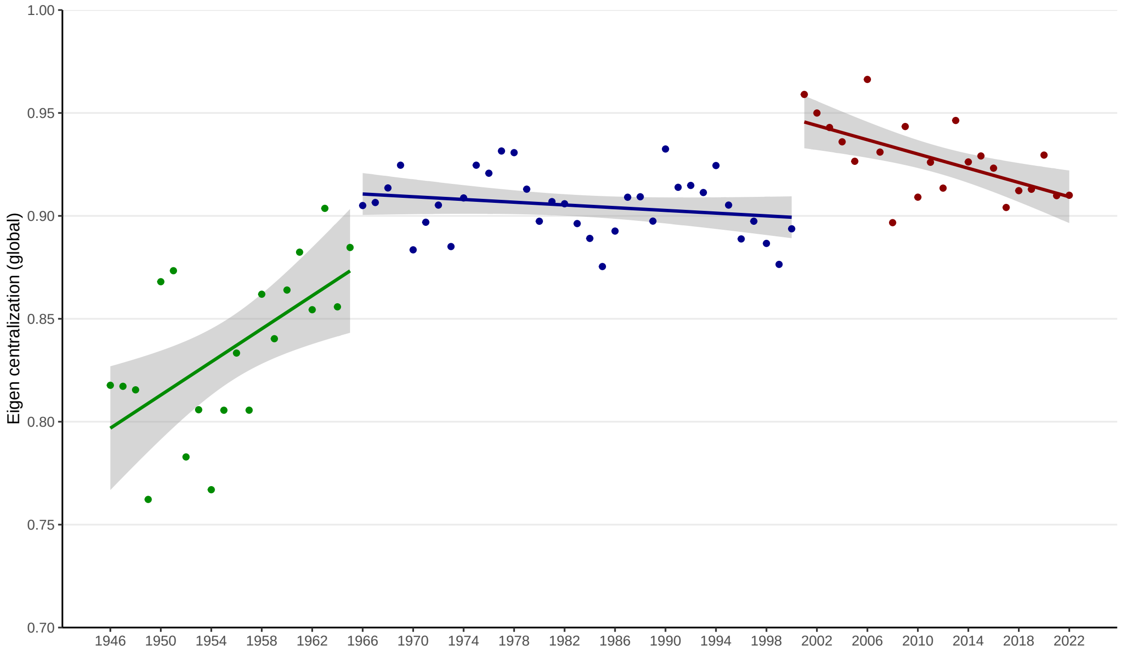
In short, eigenvector centrality[3] not only accounts for node degree, but it is also weighted on how well-connected a node's connections are (Bonacich, 1987). That is, if a member state is mentioned by a member state that is very central in the network, this is a more valuable connection (in terms of centrality score) than a mention from a less central member. Consequently, a node can have fairly high degree score, but still get low eigenvector score if the connected nodes are not well-connected themselves. As a concrete example, Chile was ranked as having the 13th highest degree score out of 112 speakers in 1971, but only 30th on eigenvector centrality because its 40 connections were not very prominent in the network of that year.

Network Centralization

Before we delve into our measure of member state (or node) importance, we summarize the structure of the annual networks in their entirety. Figure 2 shows the eigenvector centralization (Freeman, 1978) measure for each year of the UNGD. Here, higher values indicate a network with fewer and more dominant nodes, whereas lower values indicate more spread importance between the nodes.

[3]Eigenvector scores are scaled to have a range between 0 and 1, where the most central node in the network scores 1 and the

Figure 2: Trend in global eigen centralization of the annual networks of mentions. Each point is one network centralization score and the line gives the linear trend within each period. The three periods are separated by utilizing breakpoint estimation (Zeileis et al., 2003) with two breaks.



As expected, the first period of the UNGD marked by the green points and line in Figure 2 (1946-1965) saw the centralization of the network, although the absolute value is quite high from the start, grow rapidly as the two super powers – the US and Sovjet Union – raced to assert dominance over each other. In the following period (1966-2000), the yearly centralization scores are quite stable at a high level, as marked by the blue points and line. This also coincides neatly with the bipolarity often ascribed to the Cold War period. Interestingly, the breakpoint estimation identifies a break between 2000 and 2001 as the 9/11 terrorist attacks on the US was the center of attention in the 2001 UNGD.[4] Indeed, the centralization score made a big jump from 2000 to 2001. Substantively this indicates that the network is more dominated by one node; or, more towards a unipolar network. The trend for the third period is, however, that centralization is decreasing over time, but maybe not as sharply as one would expect.

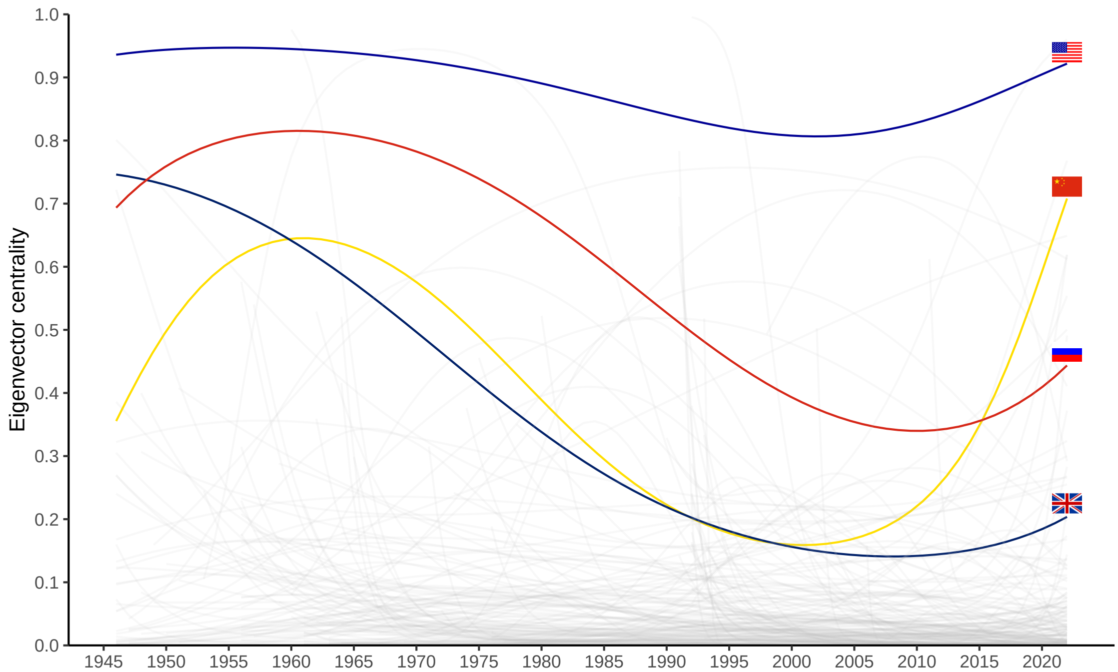
least central node(s) score 0.

[4]If estimated on three breaks, the breakpoint estimation returns 1958, 1979, and 2001, which persists from the 2 point estimation.

Node Centrality

Moving to the individual state scores of eigen centrality, Figure 3 shows the trend for member state importance throughout the period of the UNGA. As mentioned, the measure ranges from 0 to 1, but as shown in table A4-1 and Figure A3-1 in the Appendix, the variable is skewed towards the lower end of the scale. This is especially true for the latter parts of the covered period, where the attention is split among more members in the UNGA.

Figure 3: Eigenvector centrality trends in networks of UNGDs (1946-2022), with selected countries highlighted by color and other countries are gray. The lines are fitted using fractional logit model with cubic B-spline basis on time.



The trend of Figure 3 confirms the more general picture of Figure 2. Here, we highlight the trend for some key members; the USA, Russia, Great Britain, and China. All other countries are represented by gray in the background. Figure 3 shows that the USA has remained a player of large importance in the UNGD throughout the period. Early pivotal players, such as Great Britain, have gradually faltered off, whereas Russia lost influence in the aftermath of the fall of the Soviet Union but started to bounce back after the annexation of Crimea in 2016. A similar story is also observed for China, who were pivotal during the Cultural Revolution, only to lose influence during the 1970s and 1980s and then rise again during the early 2000s and onward. Finally, the networks are sensitive to salient issues in the world at different points in time, as marked by the strongly fluctuating gray lines in the background. Afghanistan, for instance, is the most central member in 1988 in the aftermath of the Soviet Union withdrawing its troops from the region; Rwanda is the most central node in 1994 following the Tutsi genocide; and, Bangladesh was the most central node in 1974, when a devastating interaction between economic crisis and natural disasters led to what is considered one of the worst famines in the 20th century (Sen, 1983).

Sentiment analysis

To separate between positively charged and negatively charged attention, we estimate the sentiment, or tone, of a mention by following Rice and Zorn (2021). Using the AFINN sentiment dictionary (Årup Nielsen, 2011) as an anchor, we build UNGD context specific sentiment dictionary from Global Vectors (GloVe) for word representation (Pennington et al., 2014). We then weight each GPE mention in the UNGD by the sentiment of the 15 words before and after each mention (30 word window), and average the sentiment for all mentions of the same country in a speech. Finally, we construct networks from only ties that are below the 25th percentile within a year of the UNGD as a negative network for that year, and above the 75th percentile as the positive network for that year.

Decomposition Design

In the following, we will decompose the centrality measure[5] by estimating a series of regression models with the eigenvector centrality measure as the dependent variable. For our main models, we use the annual scores for member states. As the measure is bound between 0 and 1, we use fractional logit models for all our models in the main part of the paper, with fixed effects on year and lagged dependent variable as controls. We also have a series of robustness models in the Appendix[6]. As for independent

[5]Because the networks based on positive and negative sentiment are naturally sparser than the full set of mentions, we use Google's PageRank centrality measure as the main variable in these regressions to avoid problems with isolated nodes or islands.

[6]See Table A6-5 for the main models without lagged dependent variable, Table A6-2 for the main models without the US, A6-6 for the main models from 1989-2022, Table A6-4 for models with change in eigenvector centrality from $t-1$ to t, Table A6-1 for models with PageRank as the depentent vaiable, and Table A6-3 for models with 5 year rolling average in eigen centrality as dependent variable.

variables, we divide these into categories of *strength through size*, *spheres of influence*, and *focal points*, as described above.

We do note that models for estimating what affects tie generation in network analysis, such as exponential random graph models (ERGM), could be fruitful in exploring specific years of the UNGD. However, these models require a complete *NxN* matrix (Kinne, 2018) of countries and years. There might be cases of states mentioning other states back in time, but this should not retroactively affect in their influence score, which is our main task here. There are, of course, also more dynamic approaches to network analysis (see Krivitsky and Handcock (2014)), but here we treat the annual networks independently from each other in an effort to maintain the interpretability, flexibility, and transferability of our approach.

Independent Variables

Strength. We use three measures as proxies for the hard power of member state: 1) Gross Domestic Product (GDP), logged, 2) total population, logged, and 3) Composite Index of National Capability (CINC). For GDP and population, we use the V-Dem dataset indicators (`e_gdp` and `e_pop`) based on Fariss et al. (2022), which has coverage for most member states[7]. The CINC variable is an index of six components distributed by the Correlates of War project's National Material Capabilities (v6.0) dataset. The individual components comprising the index are population, urban population ratio, iron and steel production, primary energy consumption, military expenditure, and military personnel, which combines to a variable ranging from 0 to 100 (we multiply the original variable by 100), signifying the share (in percentage) of the total capabilities globally (Singer et al., 1972). As we include population as its own variable, we have reconstructed the CINC variable without population.

Affinity. The affinity part of our explanatory variables consist of three sources: 1) Polyarchy, 2) trade flows, and 3) ideology. The polyarchy measure draws on the Electoral democracy index (`v2x_polyarchy`) from the V-Dem project (Coppedge et al., 2021). The variable measures to what extent the ideal of electoral democracy is fulfilled in a country in a given year, ranging from 0 to 1 where high scores indicate strong electoral democracies. In the dyadic analysis, we convert this measure to

[7]Belarus from 1946-1988, for instance, are missing although they did participate in the UNGD during those years.

be the score difference between the sender node and the target node of the dyad, so that the resulting measure ranges from -1 (sender is a lot less democratic than the target) to 1 (the sender is a lot more democratic than the target). As for trade flows, we utilize the Correlates of War project's Trade (v4.0) dataset (Barbieri et al., 2009). Because the trade data cover 1945 through 2014, the models including these variables exclude all years from 2015 and forwards. In the first analysis, we include both total imports and exports for member states, whereas we include trade flow between the sender and target nodes in the second analysis. As for ideology, we use the data provided through the Bailey et al. (2017) study, measuring state preferences from UN voting data. Typically, although temporal variations occur, the measure has member states such as North Korea and DDR on the negative extreme, and USA, Israel, and Great Britain on the positive extremes.

Focal points. In the UNGA, like in the international network, dramatic events and pertinent current topics are likely to shape both the states in themselves and what they talk about in UN General Debates. Therefore, a lot of the activity in the UNGA, as observed through states mentioning other states, is likely to be driven by the fact that some states are simply important topics on the agenda of a given year. To counter this entirely driving our results, we take three crucial factors into account, namely the occurrence of regime breakdowns, national emergencies, and whether a state is currently a member of the security council. We include a measure of proximity to regime breakdown based on the Historical Regimes Data (Djuve et al., 2020) which is a temporally fine-grained dataset that records regime change down to their specific dates. We leverage this in our analyses by taking the logged temporal distance to the most recent regime change for each state (the targets in our dyad analysis). Regime changes typically happen in processes of general turmoil, so that we might also indirectly capture unrest more generally. Moreover, we include a measure capturing the occurrence of national emergencies from the Varieties of Democracy project (Coppedge et al., 2021). This records whether a state imposed a national state of emergency at some point within a given year. Like the regime breakdown variable, we include this to capture phenomena that both make for important focal points on the UNGA agenda in addition to possibly driving changes, e.g., in the economic and political situation within the states themselves. Finally, we include a recording of security council membership to capture attention noise that is directed at certain states simply because they at the time are members of the security council and thereby are addressed more frequently in the UNGA.

Drivers of Centrality

The results of our analysis mapping the drivers of network centrality in the UNGD are shown over the 7 columns of Table 1. All model coefficients are reported in logits from a fractional logit model with year fixed effects. We also include the percentage of complete observations in each specification; the import and export data, particularly, has a lot more missing data than the other independent variables. Consequently, we introduce each variable alone with the set of controls in addition to the full model (7).

First, as shown in models (1)-(3), our strength variables are all positively associated with the centrality of member states, indicating that states with large economies, populations and military capabilities are generally more important in the UNGA network, when taking the full time period into account. All three operationalizations of the *strength through size* perspective hold when including our control variables. This general pattern is also relatively robust to alternative specifications reported in the appendix, also when we exclude USA from the sample (see Table A6-2). Given how central the US is in the UN, this latter finding is particularly important as the US is large in all of these three ways. Hence, we infer that size also matters beyond describing the role of the US.

Second, as shown in models (4)-(6), the spheres of influence-explanations also have effects on centrality that are above the significance threshold. In model (4), the democracy variable turns out to have a negative effect on centrality in the UNGA, indicating that, in general, less democratic regimes tend to receive more attention in the UNGA. In model (5) we see that imports and exports have opposite effects on centrality: larger import-economies and smaller export-economies, are more central to the network in our analysis. Finally, the variable capturing ideological position as reported in table (6), indicates that states with ideological positions located further towards the US, rather than Russia, are less central in the UNGA network. Yet, when we let the three size factors as well as the spheres of influence-factors run a horse race in model (7), GDP (log) is the only strength factor that remains significant, while both export/import, and the Ideal point-variable retain their directions and approximate sizes.

To further dig into these findings, we run analyses differentiating between positively charged and negatively charged centrality, using the PageRank centrality measure as the dependent variable. In tables 2 and 3, we show results from the same specification as our main model (see Table 1) using

	Eigenvector centrality						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.21*						0.24*
	(0.02)						(0.06)
Population (log)		0.23*					0.02
		(0.02)					(0.04)
CINC			0.07*				0.01
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				−0.28*			−0.30
				(0.09)			(0.16)
Imports (log)					0.34*		0.28*
					(0.05)		(0.05)
Exports (log)					−0.16*		−0.28*
					(0.04)		(0.04)
Ideal point						−0.06*	−0.06*
						(0.02)	(0.03)
Focal points							
Breakdown (log)	−0.01	0.07*	0.07*	0.10*	−0.01	0.09*	0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SC member	0.10	0.14*	0.21*	0.53*	0.27*	0.52*	0.05
	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
National emergency	1.23*	1.12*	1.21*	1.02*	1.20*	1.01*	1.14*
	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Centrality$_{t-1}$	4.43*	4.50*	4.38*	4.87*	4.44*	4.88*	4.26*
	(0.14)	(0.14)	(0.16)	(0.14)	(0.15)	(0.15)	(0.17)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-3.43	-5.12	-3.54	-3.52	-4.79	-3.64	-3.58
Complete obs. %	92.71	92.71	83.13	97.95	79.84	91.27	78.76
Num. obs.	8832	8832	7919	9331	7606	8694	7503
Num. groups: year	73	73	68	76	68	73	68

$^{*}p < 0.05$

Table 1: Fractional logit regressions on eigenvector centrality (1946-2022). Coefficients provided in logits with standard errors in parentheses.

only positive and negative mentions. The results are generally consistent with our main analysis, with some important exceptions. The most important exception is that the coefficient for democracy level is strongly positive in the positive network regression (Table 2), but strongly negative in the negative network regression. The negative coefficient even holds in the full model, while the coefficient for democracy in the positive sentiment model falls just short of the conventional significance threshold (p-value 0.0504). Substantively, this means that democracies are more influential – or, get more positive attention – in the network of positive mentions, whereas autocracies are more influential in the network of negative mentions.

Furthermore, the full model (7) in Table 2 shows that for the network of positive mentions, military capability retains significance, while imports does not, tilting the balance towards the strength through size-explanations. Considering the substantive impact of our explanatory factors on centrality, we refer to Figure A7-1 and Figure A7-2 in the Appendix, displaying predicted values on our centrality measure across the ranges of our explanatory variables from the models in Table 1. These show that particularly larger GDP, larger population and smaller export-reliant economies, are related to the most substantial increases in centrality score, reflecting the comparative explanatory strength of these factors.

All our models include year-fixed effects to clear out particularistic attention patterns for specific years. Yet, to further remove the impact of smaller time period particularities from our findings, we also ran our models with a 5 year rolling average-transformation of our dependent variable, displayed in the Appendix Table A6-3. This table shows that the strength through size-factors remain strong, or even stronger, whereas democracy and ideology loose their explanatory power in these models. Again, this indicates that the strength through size-explanations are more consistently supported by the data.

We also note that all focal point variables – time since regime breakdown, security council membership, and national emergency – are associated with strong effects in the expected direction in our main analysis, in Table 1. The only exception is that the regime breakdown variable is insignificant in models (1), (5), (7), and (8). To zero in on these more event-based explanations, we also ran our models with yearly changes in centrality as our dependent variable, printed in the Appendix Table A6-4. Here, our regime change and national emergency-variables outperform all the other variables, illustrating that these factors are important drivers of short-term attention patterns. As shown in the moving average-model, however, they capture much less of the longer-term trends in centrality.

	Positive Sentiment PageRank						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.17^{*}						0.14^{*}
	(0.01)						(0.07)
Population (log)		0.17^{*}					0.02
		(0.02)					(0.04)
CINC			0.07^{*}				0.04^{*}
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				0.30^{*}			0.27
				(0.09)			(0.13)
Imports (log)					0.27^{*}		0.11
					(0.05)		(0.06)
Exports (log)					-0.10^{*}		-0.12^{*}
					(0.04)		(0.05)
Ideal point						0.08^{*}	0.01
						(0.03)	(0.03)
Focal points							
Breakdown (log)	-0.04^{*}	0.03	0.01	0.01	-0.07^{*}	0.01	-0.06^{*}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
SC member	0.27^{*}	0.35^{*}	0.26^{*}	0.60^{*}	0.35^{*}	0.59^{*}	0.05
	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)
National emergency	0.49^{*}	0.39^{*}	0.36^{*}	0.56^{*}	0.44^{*}	0.37^{*}	0.37^{*}
	(0.11)	(0.11)	(0.12)	(0.11)	(0.12)	(0.10)	(0.10)
Centrality$_{t-1}$	2.10^{*}	2.20^{*}	2.14^{*}	2.43^{*}	2.17^{*}	2.39^{*}	1.98^{*}
	(0.14)	(0.14)	(0.17)	(0.13)	(0.16)	(0.14)	(0.18)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-2.85	-4.12	-2.97	-3.08	-4.13	-2.93	-3.00
Complete obs. %	74.08	74.08	67.02	77.58	64.79	72.98	63.90
Num. obs.	7057	7057	6384	7390	6172	6952	6087
Num. groups: year	73	73	68	76	68	73	68

$^{*}p < 0.05$

Table 2: Fractional logit regressions on PageRank centrality (1946-2022) based on only positive GPE mentions. Coefficients provided in logits with standard errors in parentheses.

	Negative Sentiment PageRank						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.13^*						0.24^*
	(0.01)						(0.06)
Population (log)		0.12^*					-0.09^*
		(0.01)					(0.04)
CINC			0.05^*				0.03^*
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				-0.31^*			-0.57^*
				(0.10)			(0.14)
Imports (log)					0.22^*		0.18^*
					(0.04)		(0.05)
Exports (log)					-0.11^*		-0.21^*
					(0.04)		(0.04)
Ideal point						0.01	0.04
						(0.03)	(0.04)
Focal points							
Breakdown (log)	-0.02	0.03	0.01	0.04	-0.04	0.02	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SC member	0.09	0.17^*	0.06	0.43^*	0.25^*	0.38^*	-0.02
	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)
National emergency	1.33^*	1.27^*	1.36^*	1.20^*	1.33^*	1.24^*	1.31^*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Centrality$_{t-1}$	3.27^*	3.33^*	3.17^*	3.44^*	3.18^*	3.46^*	3.01^*
	(0.14)	(0.15)	(0.15)	(0.14)	(0.16)	(0.15)	(0.16)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-3.10	-4.02	-3.17	-3.08	-3.96	-3.19	-2.10
Complete obs. %	60.93	60.93	55.46	63.58	53.05	59.79	52.23
Num. obs.	5804	5804	5283	6057	5054	5696	4975
Num. groups: year	73	73	68	76	68	73	68

$^*p < 0.05$

Table 3: Fractional logit regressions on PageRank centrality (1946-2022) based on only negative GPE mentions. Coefficients provided in logits with standard errors in parentheses.

As for our temporal expectations, we also ran our models on the UNGDs of the post-Cold War era alone, and find that our results from models (1)-(7) generally hold (see Table A6-6 in the Appendix). However, the effect of ideological standpoint as captured by our Ideal Point variable disappears in Model (7) when only modeled on the recent time period, again underlining the less consistent association between ideological standpoint and centrality.

Overall, then, the larger picture from our analysis points to the enduring influence of states that are strong by way of their size. Across our specifications, large economies are consistently more central to the international network than their counterparts. The factors we associate with spheres of influence-explanations also explain centrality in some of our models, but these factors are overall less stable. Given that the UNGD is an institution of diplomatic endeavours, we would have expected this arena to be more favorable to spheres of influence explanations. Only the effect of less export-reliant economies is the exception here, being the most substantial and consistent of the spheres of influence-factors. Yet, less export reliance is also perhaps the *spheres*-indicator that can most easily also be thought of as a feature of state strength.

Concerning the validity of our proposed approach to measuring influence, we interpret the findings from our analysis as being supportive of our assumption that centrality approximates states' relative importance. Centrality, by picking up on attention as a finite resource in the UNGA, does seem to be driven by established explanations in existing IR scholarship. The centrality measure we illustrate here is flexible and can be used in analyses beyond ours in a specification that suits various research contexts. For researchers interested in the closest approximation of *influence*, we would argue that the rolling 5-year average, with focal point controls and year-fixed effects, is the most appropriate choice. In this variant, our measure is much less driven by the types of agenda-setting incidents that one would associate with states being important topics at the General Debates, such as major political events, wars and emergencies, and can rather be interpreted as an indicator of major players in the international network. Moreover, researchers looking to avoid capturing influence driven by e.g. naming and shaming practices(Terman and Byun, 2022), can include only positively charged attention by way of our sentiment-based subdivision of mentions.

Conclusion

In this paper, we have proposed an new approach to measuring influence in the international network of states and showed how this approach highlights important trends in international relations, as well as capturing widely used indicators of state influence in global politics. More specifically, we have argued that connections through attention in the UNGA gives a unique opportunity for approximating how influential states are in the international network.

To arrive at our centrality measure, we first extracted named entities from speeches given during the UN General Debates using Named Entity Recognition. From the entities extracted, we built annual directed networks of state mentions and from these networks calculated the centrality of each node for each year. The result is a country-year dataset that contains information on the relative yearly centrality of each UNGA member across the covered time period, 1946-2022.

Then, to explain patterns of global politics in aggregate, we systematize large and influential explanations of influence in the international system into two major categories, namely, explanations that emphasize *strength through size* and explanations that emphasize *spheres of influence*. By grouping three main explanatory variables into each of these categories and modeling their effects on centrality in the UNGA network, we find that particularly the explanations emphasizing strength through the size of states' economies and populations receive ample support in our analysis - also when excluding the US from our sample. It also seems, from our analyses, that states who are large importers, rather than large exporters, are centers of attention in the UNGA to a much larger degree than their counterparts. The remaining spheres of influence-explanations are less stable across our employed range of modeling specifications.

In terms of transferrability, our approach contributes in several ways. First of all, the UNGD provides a unique context of equal participation access, which is not necessarily the case for other possible approximations (such as indicators based on embassy placement in dyads (Duque, 2018)). Further, this centrality measure can be useful in applications where influence appears as an independent variable, when researchers seek to explain various other features or trends in the international system, such as states' conflict behavior. Finally, the more general approach we apply here – building entity networks from text – is transferable to an unrestrained range of ot her political arenas, as long as attention in those arenas is a limited resource (at least to some extent), thereby making the connection we make here between influence and relative attention plausible.

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Online supporting information

Table of contents:

A1. spaCy NER details

spaCy returns either single-token entities (`GPE_B`) or a multi-token entities (`GPE_B + GPE_I`). For instance, consider this small segment from the 2016 speech by Mr. Bruno Eduardo Rodríguez Parrilla, the Cuban Minister for Foreign Affairs:

> [W]e will continue to present the draft resolution entitled "Necessity of ending the economic, commercial and financial embargo imposed by the United States of America against Cuba" for consideration by the Assembly.

In Table A1-1 (a), parts of this segment is shown, as it is returned by the spaCy parser. Here, there are two identified entities ("the United States of America" and "Cuba"). We concatenate these multi-token entities, stripped of preceding function words ("the"), into one entity and then extract only the entities from the text. As such, we would extract two entities from the example in Table A1-1 (a): "United States of America" and "Cuba".[8]

Next, we map these entities to their respective ISO-3166-3 codes through the `countrycode` package for R (Arel-Bundock et al., 2018) and set up pairwise counts of the country holding the speech and the named entities in that speech. Importantly, we only keep entities that held a speech in a given session on both sides of the dyads. The final product, as shown in Table A1-1 (b) for the example, is the mention counts of other countries from the speaker country. The the speaker and target countries in a given year is the vertex set and the count between them the edge set of our graph models (see below). Importantly, the edges in our graph are *directed*; for instance, Cuba mentioned the USA 5 times in 2016, as shown in Table A1-1, but the USA only mentioned Cuba twice. Consequently, these edge between Cuba and USA is not the same as the edge between USA and Cuba[9], which would be the case with *undirected* dyads. These dyads comprise the foundation for

Figure A1-1a shows the (logged) amount of entities the speaker (or sender) mentions, with the the median count as white, the lower as orange, and the higher as cyan.[10]. Here, Russia (including the Soviet Union) is the largest contributor (3401 or 2.3% of all entity mentions), followed by Ukraine and

[8] Do note that we exclude mentions of ones own country. In the example, this is the case for "Cuba".

[9] $Cuba \rightarrow USA \neq USA \rightarrow Cuba$

[10] Of course, maps change over time, so this is only showing countries present in the current world map. Countries that are no longer present in the world will not be shown in these figures.

Table A1-1: Cuban UNGD speech in 2016 example

(a) Extract of speech

	token	pos	entity
1546	Necessity	NOUN	
1547	of	ADP	
1548	ending	VERB	
1549	the	DET	
1550	economic	ADJ	
1551	,	PUNCT	
1552	commercial	ADJ	
1553	and	CCONJ	
1554	financial	ADJ	
1555	embargo	NOUN	
1556	imposed	VERB	
1557	by	ADP	
1558	the	DET	GPE_B
1559	United	PROPN	GPE_I
1560	States	PROPN	GPE_I
1561	of	ADP	GPE_I
1562	America	PROPN	GPE_I
1563	against	ADP	
1564	Cuba	PROPN	GPE_B

(b) Country dyads

year	session	send_country	target_country	count_gpe
2016	71	CUB	USA	5
2016	71	CUB	VEN	2
2016	71	CUB	BRA	1
2016	71	CUB	RUS	1
2016	71	CUB	SYR	1
2016	71	CUB	PSE	0

Figure A1-1: Target and sender counts in UNGDs (1946-2022)

(a) Senders (b) Targets

Belarus – these three members combined account for ~ 5.7% of the entity mentions throughout the period. In total, there were 146618 mentions between all member states across the entire period. These mentions make up the edges in our network of mentions.

Figure A1-1b shows the (logged) amount of mentions countries have received throughout the period. As is evident from the figure, the USA (17389), Israel (12918) and Russia (8945, including the Soviet Union) have been the source of much attention throughout the period; combined, these three member states have assembled more than 25% of the entity mentions in the UNGD. As for the countries with less mentions, smaller (often African) countries such as the Seychelles, São Tomé & Príncipe, and Turkmenistan are the least mentioned countries. Some of this does, of course, come down to these countries becoming members at a later stage, but most of them are also least mentioned per year they have participated in the UNGD.

A key take-away here is that the distribution of what states mention other states is a lot more even than what states receive mentions. We will discuss this more in depth in the analysis.

A2. NER descriptives

Table A2-1: spaCy NER tags with corpus counts.

Tag	Description	Count
CARDINAL	Numerals that do not fall under another type	249047
DATE	Absolute or relative dates or periods	207073
EVENT	Named hurricanes, battles, wars, sports events, etc.	32345
FAC	Buildings, airports, highways, bridges, etc.	4403
GPE	Countries, cities, states	438206
LANGUAGE	Any named language	935
LAW	Named documents made into laws.	67651
LOC	Non-GPE locations, mountain ranges, bodies of water	99699
MONEY	Monetary values, including unit	6189
NORP	Nationalities or religious or political groups	155044
ORDINAL	"first", "second", etc.	55755
ORG	Companies, agencies, institutions, etc.	413083
PERCENT	Percentage, including "%"	9609
PERSON	People, including fictional	51995
PRODUCT	Objects, vehicles, foods, etc. (not services)	758
QUANTITY	Measurements, as of weight or distance	2965
TIME	Times smaller than a day	3273
WORK_OF_ART	Titles of books, songs, etc.	3576

A3. Centrality – Descriptives

Figure A3-1: Eigenvector and PageRank centrality distribution and correlation (line).

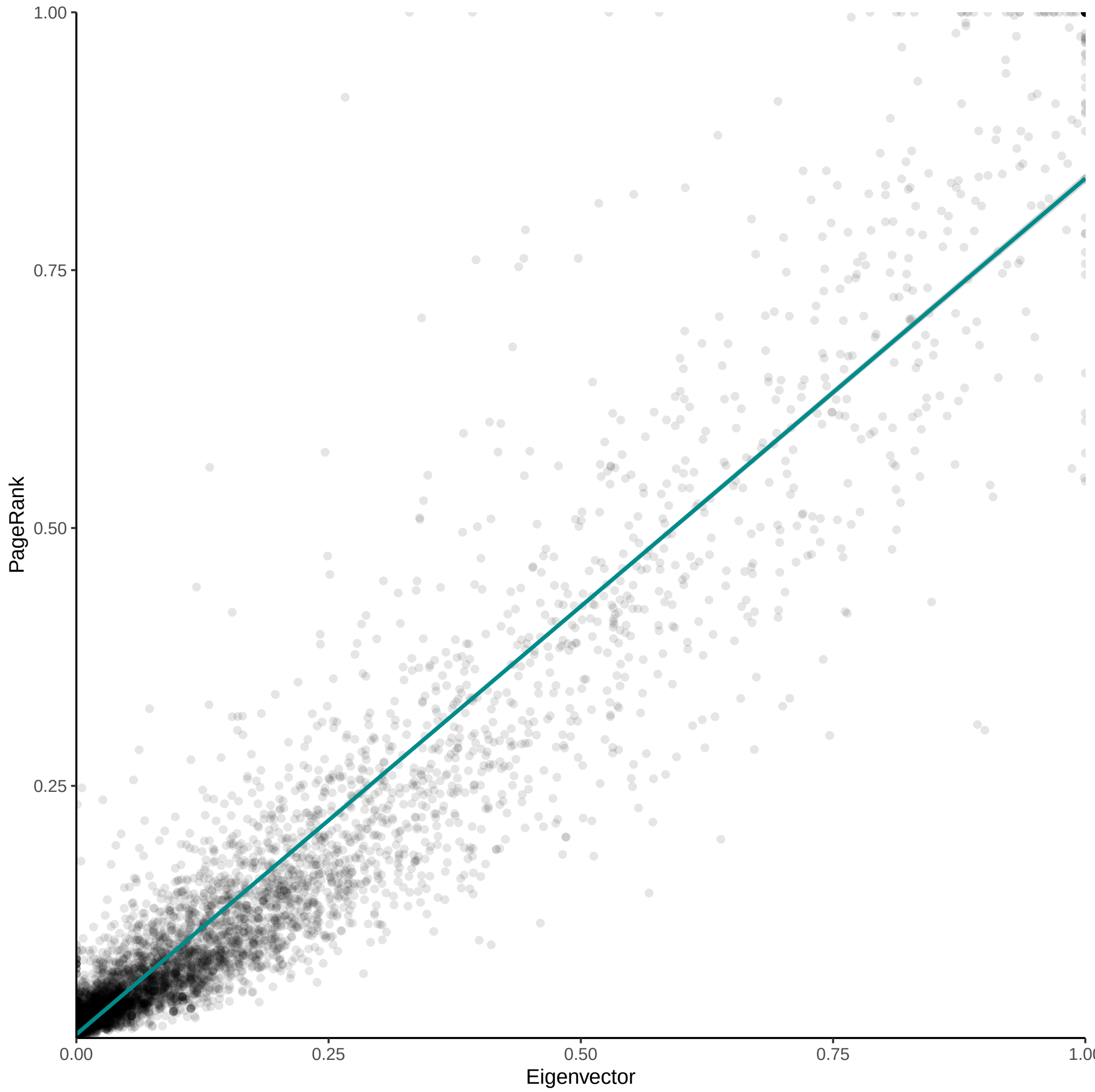


Figure A3-2: Top 50 countries in average eigen centrality (1946-2022).

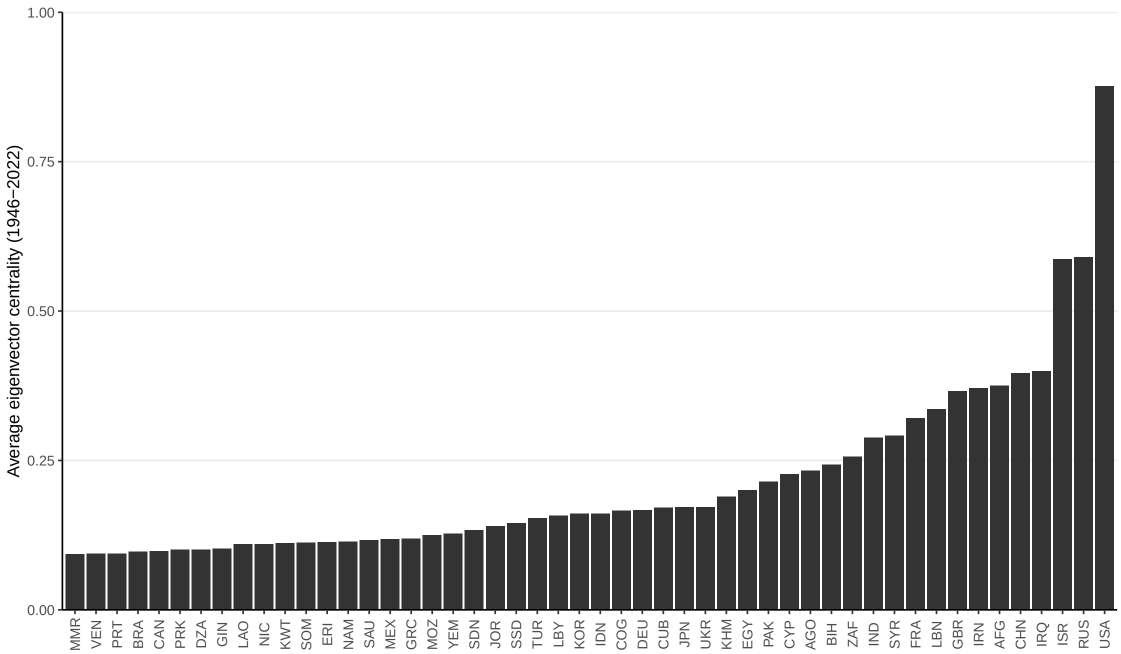


Table A3-1: List of all centrality measures provided in the data of centrality trends in the UNGD.

Variable Name	Measure	Description	Reference
`eigen_cent`	Eigenvector	Measures influence of a node in a network	Bonacich (1987)
`pagerank_cent`	PageRank	Evaluates the importance of nodes	Brin and Page (1998)
`in_degree`	In-Degree	Counts incoming connections to a node	Csardi and Nepusz (2006)
`out_degree`	Out-Degree	Counts outgoing connections from a node	Csardi and Nepusz (2006)
`harm_cent`	Harmonic	Focuses on the sum of the reciprocal	Marchiori and Latora (2000)
`close_cent`	Closeness	Indicates how close a node is to others	Freeman (1978)
`betw_cent`	Betweenness	Measures node's role in information flow	Brandes (2001)
`hub_cent`	Hub	Identifies nodes acting as hubs	Kleinberg (1999)
`auth_cent`	Authority	Identifies nodes acting as authorities	Kleinberg (1999)

Centralization

All measures of centralization in the `igraph` package follows the formula:

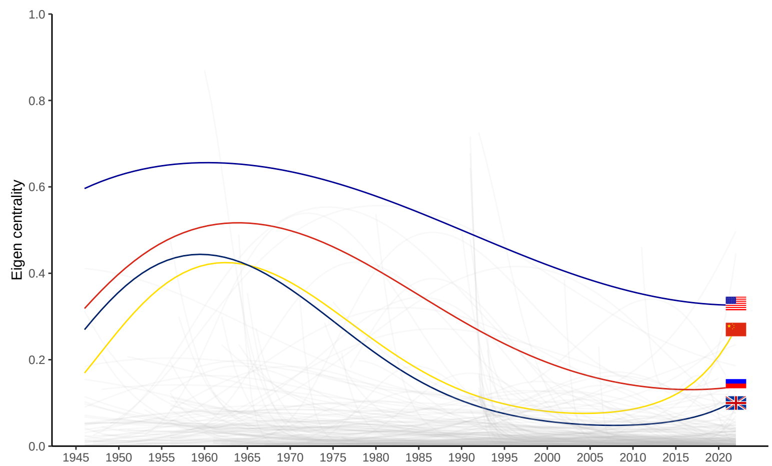
$$C(G) = \sum_v (max_w c_w - c_v)$$

where C_v is the centrality of vertex $_v$.

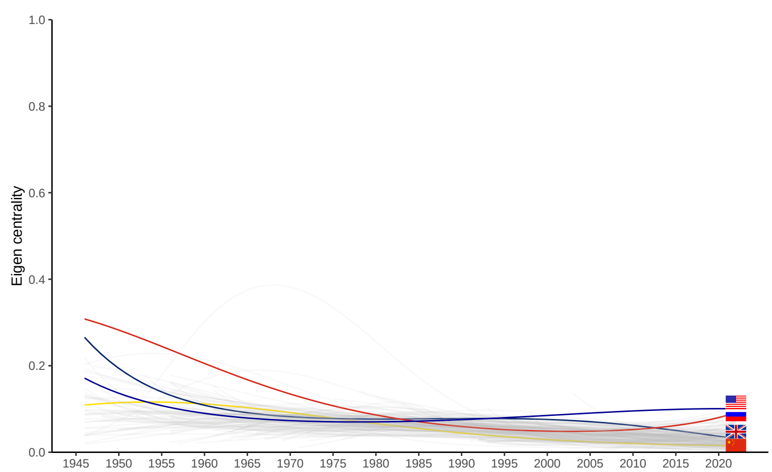
Degree Centrality

Figure A3-3: In-degree and out-degree trends in the UNGD networks.

(a) Inwards centrality trend (1946-2022)



(b) Outwards centrality trend (1946-2022)



A4. Descriptives

Table A4-1: Descriptive statistics for the analysis of member state importance in the UNGDs.

Variable	N	Min	Median	Mean	Max	SD
Eigenvector centrality	9526	0.00	0.02	0.10	1.00	0.19
GDP (log)	9026	-5.16	0.05	0.20	5.79	1.97
Population (log)	9026	1.90	6.77	6.75	11.91	1.68
CINC	8107	0.00	0.00	0.01	0.42	0.03
Polyarchy	9526	0.01	0.38	0.44	0.92	0.28
Imports (log)	7771	-0.69	7.73	7.90	14.74	2.28
Exports (log)	8021	-5.81	7.28	7.51	14.85	2.56
Ideal point	8877	-2.96	-0.18	-0.01	3.15	0.97
Security Council member	9526	0.00	0.00	0.11	1.00	0.31
National emergency	9505	0.00	0.00	0.16	1.00	0.22
Breakdown (log)	9524	-2.50	2.67	2.52	5.61	1.16
Centrality (lag)	9351	0.00	0.02	0.10	1.00	0.19

A5. Variable coverage

Table A5-1: List of coverage and source of all variables used in the drivers of centrality anaysis. Variables without source are made

Variable	Name in dataset	Years	Source
Eigenvector centrality	`eigen_cent`	1946-2022	–
GDP (log)	`e_gdp`	1946-2019	Fariss et al. (2022)
Population (log)	`log_pop`	1946-2019	Fariss et al. (2022)
CINC	`cinc_nopop`	1946-2014	Singer et al. (1972)
Polyarchy	`v2x_polyarchy`	1946-2022	Coppedge et al. (2021)
Ideal point	`ideal_point`	1946-2019	Bailey et al. (2017)
Imports (log)	`imports`	1946-2014	Barbieri et al. (2009)
Exports (log)	`exports`	1946-2014	Barbieri et al. (2009)
Breakdown (log)	`breakdown_y`	1946-2022	Djuve et al. (2020)
Security Council member	`sc_member`	1946-2022	UN website
National emergency	`emergency`	1946-2022	Coppedge et al. (2021)
Eigenvector centrality (lag)	`eigen_cent_lag`	1947-2022	–

A6. Centrality regression – alternative specifications

	PageRank centrality						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.17*						0.19*
	(0.01)						(0.05)
Population (log)		0.18*					−0.00
		(0.02)					(0.03)
CINC			0.07*				0.03*
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				−0.18*			−0.19
				(0.07)			(0.12)
Imports (log)					0.30*		0.23*
					(0.04)		(0.05)
Exports (log)					−0.15*		−0.23*
					(0.04)		(0.03)
Ideal point						−0.02	−0.03
						(0.02)	(0.03)
Focal points							
Breakdown (log)	−0.01	0.06*	0.05*	0.07*	−0.02	0.07*	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
SC member	0.18*	0.22*	0.21*	0.53*	0.32*	0.51*	0.06
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)
National emergency	1.15*	1.05*	1.17*	1.03*	1.12*	0.99*	1.09*
	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
Centrality$_{t-1}$	4.08*	4.17*	4.00*	4.47*	4.11*	4.47*	3.87*
	(0.12)	(0.12)	(0.14)	(0.12)	(0.13)	(0.12)	(0.15)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-3.32	-4.66	-3.43	-3.41	-4.49	-3.48	-3.31
Complete obs. %	92.71	92.71	83.13	97.95	79.84	91.27	78.76
Num. obs.	8832	8832	7919	9331	7606	8694	7503
Num. groups: year	73	73	68	76	68	73	68

$^*p < 0.05$

Table A6-1: Fractional logit regressions on PageRank centrality (1946-2022). Coefficients are in logits with standard errors in parentheses.

	Eigenvector centrality						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.21^*						0.24^*
	(0.02)						(0.06)
Population (log)		0.22^*					0.02
		(0.02)					(0.04)
CINC			0.08^*				0.00
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				-0.33^*			-0.31
				(0.09)			(0.16)
Imports (log)					0.33^*		0.28^*
					(0.05)		(0.05)
Exports (log)					-0.16^*		-0.28^*
					(0.04)		(0.04)
Ideal point						-0.08^*	-0.07^*
						(0.02)	(0.03)
Focal points							
Breakdown (log)	-0.01	0.07^*	0.07^*	0.10^*	-0.01	0.09^*	0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SC member	0.09	0.12^*	0.19^*	0.49^*	0.25^*	0.47^*	0.06
	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
National emergency	1.23^*	1.11^*	1.22^*	1.01^*	1.19^*	1.01^*	1.13^*
	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Centrality$_{t-1}$	4.43^*	4.47^*	4.40^*	4.80^*	4.42^*	4.80^*	4.27^*
	(0.15)	(0.15)	(0.17)	(0.15)	(0.16)	(0.16)	(0.17)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-3.43	-5.09	-3.56	-3.49	-4.77	-3.63	-3.63
Complete obs. %	92.70	92.70	83.09	97.95	79.78	91.24	78.69
Num. obs.	8759	8759	7851	9255	7538	8621	7435
Num. groups: year	73	73	68	76	68	73	68

$^*p < 0.05$

Table A6-2: Fractional logit regressions on eigenvector centrality, excluding USA from the time series.

	Eigenvector centrality (roling average, 5 years)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.38^{*}						0.40^{*}
	(0.01)						(0.07)
Population (log)		0.38^{*}					-0.07^{*}
		(0.01)					(0.03)
CINC			0.20^{*}				0.12^{*}
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				-0.10			-0.23
				(0.11)			(0.16)
Imports (log)					0.78^{*}		0.52^{*}
					(0.04)		(0.05)
Exports (log)					-0.43^{*}		-0.54^{*}
					(0.04)		(0.03)
Ideal point						0.08^{*}	-0.02
						(0.02)	(0.04)
Focal points							
Breakdown (log)	-0.12^{*}	0.03	-0.02	0.03	-0.16^{*}	0.00	-0.10^{*}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
SC member	0.56^{*}	0.71^{*}	0.36^{*}	1.30^{*}	0.83^{*}	1.26^{*}	0.18^{*}
	(0.04)	(0.04)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)
National emergency	1.70^{*}	1.51^{*}	1.63^{*}	1.61^{*}	1.61^{*}	1.52^{*}	1.51^{*}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-2.65	-5.48	-2.78	-2.78	-5.43	-2.76	-2.12
Complete obs. %	94.19	94.19	83.95	99.81	80.87	92.77	79.81
Num. obs.	8313	8313	7409	8809	7138	8188	7044
Num. groups: year	70	70	65	73	65	70	65

$^{*}p < 0.05$

Table A6-3: Fractional logit regressions on rolling 5 year average of eigenvector centrality.

	Eigenvector centrality (Δ)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	−0.08						−0.12
	(0.12)						(0.45)
Population (log)		0.02					0.17
		(0.15)					(0.32)
CINC			−0.02				−0.01
			(0.10)				(0.10)
Spheres of influence							
Polyarchy				−1.10			−0.66
				(0.64)			(1.06)
Imports (log)					−0.33		−0.22
					(0.37)		(0.47)
Exports (log)					0.18		0.16
					(0.31)		(0.31)
Ideal point						−0.20	0.02
						(0.20)	(0.27)
Focal points							
Breakdown (log)	0.79^*	0.76^*	0.79^*	0.78^*	0.82^*	0.78^*	0.84^*
	(0.21)	(0.20)	(0.22)	(0.21)	(0.25)	(0.21)	(0.24)
SC member	0.15	−0.04	0.04	0.14	0.15	−0.02	−0.09
	(0.53)	(0.51)	(0.50)	(0.55)	(0.59)	(0.60)	(0.53)
National emergency	3.32^*	3.32^*	3.82^*	3.14^*	3.58^*	3.00^*	3.13^*
	(0.96)	(0.98)	(1.00)	(0.91)	(1.04)	(0.90)	(1.00)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-2.75	-2.81	-2.82	-2.23	-1.68	-2.68	-3.14
Complete obs. %	92.71	92.71	83.13	97.95	79.84	91.27	78.76
Num. obs.	8832	8832	7919	9331	7606	8694	7503
Num. groups: year	73	73	68	76	68	73	68

$^*p < 0.05$

Table A6-4: Fractional logit regressions on change in egenvector centrality from $t-1$ to t.

	Eigenvector centrality						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.38*						0.37*
	(0.02)						(0.09)
Population (log)		0.38*					−0.07
		(0.02)					(0.05)
CINC			0.21*				0.13*
			(0.01)				(0.01)
Spheres of influence							
Polyarchy				−0.11			−0.18
				(0.13)			(0.18)
Imports (log)					0.72*		0.49*
					(0.05)		(0.06)
Exports (log)					−0.37*		−0.49*
					(0.04)		(0.04)
Ideal point						0.06	−0.05
						(0.03)	(0.04)
Focal points							
Breakdown (log)	−0.11*	0.03	−0.01	0.05	−0.13*	0.03	−0.08*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SC member	0.52*	0.70*	0.29*	1.29*	0.80*	1.25*	0.08
	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.04)	(0.06)
National emergency	2.03*	1.83*	2.00*	1.93*	1.98*	1.87*	1.90*
	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-2.74	-5.51	-2.90	-2.88	-5.52	-2.89	-2.51
Complete obs. %	94.51	94.51	84.88	99.76	81.36	92.95	80.17
Num. obs.	9003	9003	8086	9503	7750	8854	7637
Num. groups: year	74	74	69	77	69	74	69

$^{*}p < 0.05$

Table A6-5: Fractional logit regressions on eigenvector centrality, excluding $t - 1$ as a control.

	Eigenvector centrality						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strength through size							
GDP (log)	0.21*						0.23*
	(0.02)						(0.10)
Population (log)		0.24*					0.05
		(0.03)					(0.07)
CINC			0.07*				−0.02
			(0.02)				(0.01)
Spheres of influence							
Polyarchy				−0.64*			−1.17*
				(0.10)			(0.23)
Imports (log)					0.30*		0.31*
					(0.06)		(0.08)
Exports (log)					−0.13*		−0.26*
					(0.05)		(0.05)
Ideal point						−0.10*	0.08
						(0.04)	(0.06)
Focal points							
Breakdown (log)	−0.02	0.06	0.05	0.09*	−0.03	0.08*	−0.01
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
SC member	0.10	0.15*	0.31*	0.62*	0.23*	0.61*	0.09
	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.10)
National emergency	1.21*	1.08*	1.26*	0.98*	1.31*	0.97*	1.03*
	(0.16)	(0.16)	(0.17)	(0.16)	(0.18)	(0.18)	(0.18)
Centrality_{t-1}	4.72*	4.78*	4.67*	5.13*	4.67*	5.23*	4.46*
	(0.23)	(0.21)	(0.25)	(0.20)	(0.25)	(0.25)	(0.26)
Year FE	✓	✓	✓	✓	✓	✓	✓
Mean FE	-3.48	-5.35	-3.65	-3.45	-5.02	-3.77	-3.75
Complete obs. %	90.41	90.41	74.68	99.46	71.77	89.36	70.75
Num. obs.	4989	4989	4121	5488	3960	4931	3904
Num. groups: year	31	31	26	34	26	31	26

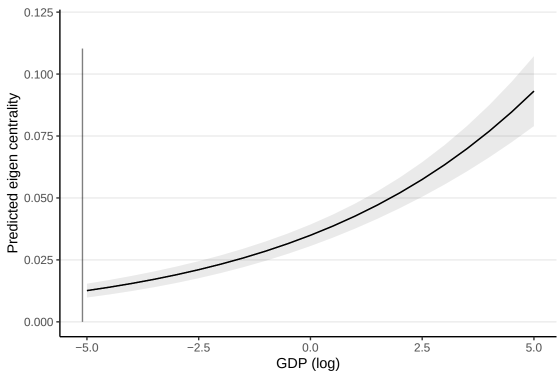
$^{*}p < 0.05$

Table A6-6: Fractional logit regressions on eigenvector centrality (1989-2022).

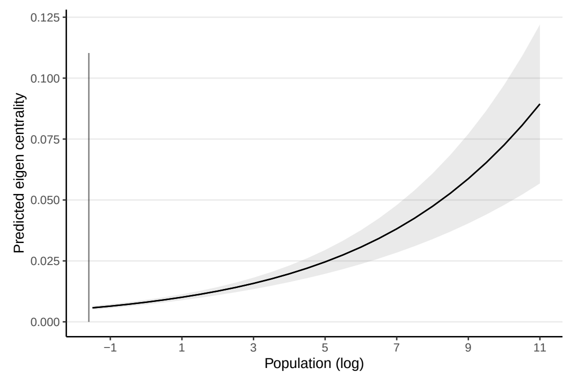
A7. Effect plots

Figure A7-1: Predicted eigenvector centrality over variation in *strenght through size* indicators. The vertical line at the left edge idicates the span from first and third quantiles of the real eigenvector centrality variable.

(a) GDP (model 1)



(b) Population (model 2)



(c) CINC (model 3)

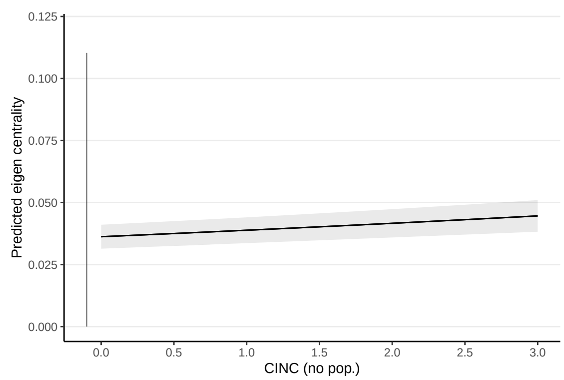
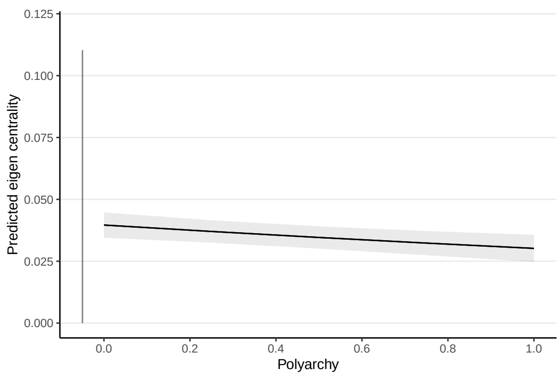
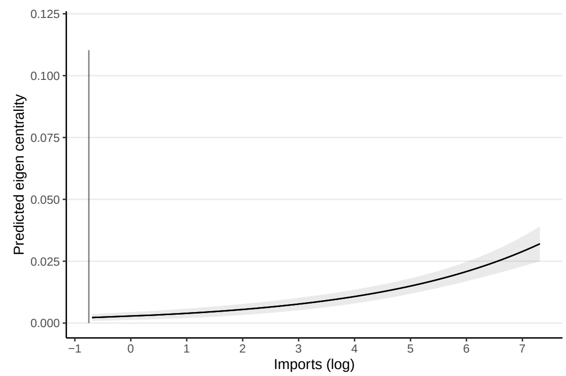


Figure A7-2: Predicted eigenvector centrality over variation in *spheres of influence* indicators. The vertical line at the left edge idicates the span from first and third quantiles of the real eivenvector centrality variable.

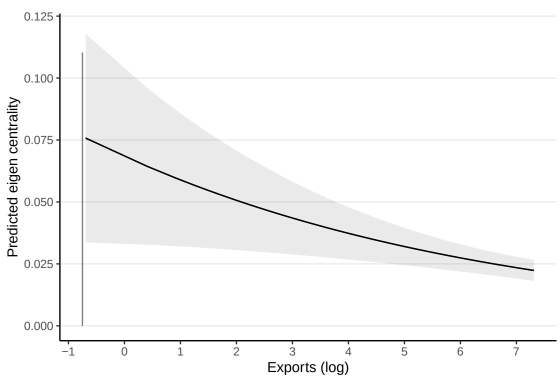
(a) Polyarchy (model 4)



(b) Imports (model 5)



(c) Exports (model 6)



(d) Ideology (model 6)