Network Science (2025), **13**, e20, 1–22
doi:10.1017/nws.2025.10016

RESEARCH ARTICLE

A "broken egg" of U.S. Political Beliefs: Using response-item networks (ResIN) to measure ideological polarization

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Abstract

Belief network analysis (BNA) has enabled major advances in the study of belief systems, capturing Converse's understanding of the interdependence among multiple beliefs (i.e., constraint) more intuitively than many conventional statistics. However, BNA struggles with representing political divisions that follow a spatial logic, such as the "left–right" or "liberal-conservative" ideological divide. We argue that Response Item Networks (ResINs) have important advantages for modeling political cleavage lines as they organically capture belief systems in a latent ideological space. In addition to retaining many desirable properties inherent to BNA, ResIN can uncover ideological polarization in a visually intuitive, theoretically grounded, and statistically robust fashion. We demonstrate the advantages of ResIN by analyzing ideological polarization with regard to five hot-button issues from 2000 to 2020 using the American National Election Studies (ANES), and by comparing it against an equivalent procedure using BNA. We further introduce system-level and attitude-level polarization measures afforded by ResIN and discuss their potential to enrich the analysis of ideological polarization. Our analysis shows that ResIN allows us to observe much more detailed dynamics of polarization than classic BNA approaches.

Keywords: belief network analysis; political polarization; ideological alignment; item response theory; latent ideology inference

1. Introduction

Although more than eight decades have passed since Philip Converse famously advocated for analyzing political ideologies as networks of interrelated beliefs, scholars have only recently begun to model political attitude systems as dedicated statistical networks (e.g., Boutyline and Vaisey, 2017; Brandt et al., 2019; DellaPosta, 2020; Fishman and Davis, 2022; Warncke, 2025). By conceptualizing individuals' opinions on political issues as nodes and the associative strength between them as weighted edges, belief network analysis (BNA) not only provides a methodological framework that well-aligns with Converse's original conception, but also allows researchers to rigorously investigate ideologies as wholistic, system-level phenomena. However, BNA does not adequately capture the spatial dimension of political ideologies, that is, their role in representing abstract dividing lines–such as the familiar left–right or liberal-conservative spectrum–that demarcate political conflict within societies (Schattschneider, 1952; Free and Cantril, 1967; Lipset et al., 1967;

Jost et al., 2008; Ellis and Stimson, 2012; Hooghe and Marks, 2018; Federico, 2019). Since key processes of ideological realignment and polarization are often framed as positional shifts along such dividing lines, BNA offers only limited insights into the structural transformations within belief systems during such dynamics.

We aim to bridge this gap by applying Response Item Networks (ResIN)—a novel class of belief network models operating at the issue response level—to the study of ideological polarization. While previous works on ResIN have either focused on validating its methodology (Carpentras et al., 2024), or applied it to static phenomena such as vaccination attitudes (Carpentras et al., 2022) and social identity construction (Lüders et al., 2024), our focus here is to explore ResIN's potential to understand political attitude polarization as a dynamic, system-wide process (cf. Durrheim and and (2025)), without assuming the existence of latent variables. Using six waves of American National Election studies (ANES) from 2000 to 2020, we demonstrate ResIN's capacity in capturing multi-level shifts in U.S. belief systems during ideological polarization, presenting the spatial transition from a largely unstructured, to a fully structured, polarized opinion space.

By visualizing the polarization process among five key political issues in the U.S., we notice that the underlying dynamic resembles the "breaking of an egg," that is, the transformation of an initially amorphous, or egg-shaped belief system into a single, polarized, left–right ideological dimension. Furthermore, we show how ResIN-based metrics can enhance our understanding of this process both at the system and the attitude level. Our proposed system-level measures are able to reveal increasing trends both in belief constraint and polarization, as well as interesting patterns of partisan asymmetries that underlie both processes. At the attitude level, our proposed statistics can identify specific roles different attitudes play in constraining belief systems of different partisan groups as well as which attitudes build bridges between them. We argue that these results and measurements cannot be easily observed in standard BNA, demonstrating that ResIN offers a novel angle to explore ideological polarization with belief networks.

Our contributions to the fields of BNA and ideological polarization are twofold. First, by applying ResIN to study political polarization, our work adds to the relatively scarce literature on conceptualizing polarization in belief networks. Taking this perspective is promising for uncovering psychological mechanisms that drive ideological polarization. Second, our measures at the system and attitude levels evaluate the degree of polarization across various facets in one cohesive framework. Using ResIN, we are able to connect the mental maps of how individuals organize political attitudes, with the collective patterns of how the public structurally constrains different beliefs. A model that encodes this individual-collective nexus, which is a crucial aspect for deconstructing ideological polarization (Kish Bar-On et al., 2024), may allow us to synthesize insights of polarization studies at different levels.

The remainder of this paper is organized as follows. In Section 2.1, we review the notion of political belief system since its introduction by Converse (1964), articulating its definition and connections with the formation of ideologies in the mass public. We then refresh the conceptualization of ideological constraint and polarization and discuss the strengths and limitations of existing BNA frameworks in Section 2.2. Then, in Section 3, we describe the dataset for this study, specify the steps of constructing ResIN snapshots, and introduce different measures of ideological constraint and polarization afforded by ResIN. We show the results and demonstrate ResIN's advantages over BNA in Section 4, acknowledge the limitations in Section 5, and conclude with final remarks in Section 6.

2. Related works

2.1 Belief systems and ideologies

> Certain postures tend to co-occur and this co-occurrence has obvious roots in the configuration of interest and information that characterize particular niches in the social structure, . . ., not simply because both are in the interest of the person holding a

> particular status but for more abstract and quasi-logical reasons developed from a coherent worldview as well. It is this type of constraint that is closest to the classic meaning of the term "ideology" (8).
> – Converse, The nature of belief systems in mass publics (1964).

Political attitudes rarely exist in isolation. For instance, support for increasing government spending on social welfare is usually linked to favoring higher income taxes for wealthy citizens in many Western democracies (Roosma et al., 2013). Public opinion scholars have long relied on the concept of constraint, that is, the functional interdependence between two or more issue positions (Converse, 1964), to study the prevalence of connected political beliefs at the individual (Zaller, 1992; Kuklinski and Peyton, 2007) and the collective level (Boutyline and Vaisey, 2017; Brandt and Sleegers, 2021; Warncke, 2025). Viewed through this lens, an ideology, then, is a package of constrained beliefs that have been logically, quasi-logically, or socially developed to form an integrated framework (Converse, 1964; Federico, 2019).

Building upon this conceptualization, our understanding of mass ideologies further rests on two key premises. First, we view ideology as a latent construct at a level of higher abstraction, which stems from, and might exert influence on multiple issue positions and identities (Jost et al., 2008; Federico, 2019). Yet, ideologies and issue positions are not always aligned (Free and Cantril, 1967; Ellis and Stimson, 2012; Groenendyk et al., 2023); ideological misalignment can have broad and meaningful implications for understanding political cognition and behavior (Zaller, 1992; Converse, 1964; Ellis and Stimson, 2012; Kinder and Kalmoe, 2017). We therefore refrain from assuming any alignment between ideologies and issue positions a priori, that is, defining ideological orientation based on particular issue positions, and vice versa (e.g., fixating opposition to redistribution as a right-wing attitude or right-wing identity to entail opposing redistribution). Furthermore, we explicitly acknowledge that the way ideologies and issue positions align may vary over time and across different political contexts (Johnston and Ollerenshaw, 2020). We, therefore, believe it particularly beneficial to let ideological structure emerge organically from observed co-endorsement patterns within political attitude data.

Understanding why variation in ideological alignment exists is key to our second premise: we consider ideologies as socially constructed attitude bundles. This assertion rests on the well-documented observation that the co-occurrence of response patterns is often shaped by an underlying social structure, including socialized partisan leanings (Campbell et al., 1960; Converse, 1964; Green et al., 2004; Baldassarri and Gelman, 2008; Mason, 2015). For example, support for social security policies is far from randomly distributed across the population; it is significantly more prevalent among Democrats than among Republicans. The collective identity formed by social and partisan groups often serves as ideological heuristics when individuals try to position themselves on a new issue or update their former beliefs. For instance, when a Democrat positions themself on a new issue, they might first take into account how other Democrats position themselves on this very issue. Consequently, ideological alignment implies more than a sorting process along various ideological dimensions. It should also be understood as a consolidation and polarization process in which political beliefs can become fused with group identities (ibid.).

2.2 Ideological polarization and belief network analysis (BNA)

Despite substantial research effort investigating political polarization, debates among social and political scientists persist regarding its overall trends in the mass public and the underlying mechanisms that drive it (Baldassarri and Bearman, 2007; Abramowitz and Saunders, 2008; Abramowitz, 2010; Fiorina et al., 2011; Federico, 2019). One reason such debates persist is that ideological polarization has been conceptualized and measured in various different ways. Two influential conceptualizations of polarization are divergence and alignment (Lelkes, 2016). Divergence describes a process of people moving apart from one another toward the extreme ends of an ideological dimension, such as the left–right spectrum (Fiorina et al., 2011). Alignment, by contrast, means that people develop ideologically coherent beliefs (i.e., constraint; Converse (1964)) because their partisan identities are increasingly aligned with political issue positions (i.e., partisan sorting Abramowitz and Saunders (2005)). Regarding alignment, a system is considered strongly polarized if people's position on one issue or their partisan identity can be used to reliably predict their position on various other issues. Conversely, a system in which people's position on one issue or their partisan identity is a weak predictor of issue positions would be considered less polarized.

Over the past few decades, researchers have not seen a vast divergence along many political issues in the United States (DiMaggio et al., 1996; Hill and Tausanovitch, 2015; Lelkes, 2016); however they do observe alignment in terms of the increasingly pronounced partisan identities (DellaPosta et al., 2015; Baldassarri and Gelman, 2008) that now have stronger ties with political beliefs (Levendusky, 2009; Han, 2011; DellaPosta, 2020). Our study uses a belief network perspective to better understand this process.

To assess the degree of ideological alignment, researchers have explored linear methods (e.g., Mason, 2015; Davis and Dunaway, 2016; Baldassarri and Gelman, 2008), and more recently belief network analysis (BNA) (e.g., Boutyline and Vaisey, 2017; Brandt et al., 2019; Fishman and Davis, 2022). Following Converse's idea of belief constraint, BNA operationalizes belief systems by representing issues (e.g., abortion restrictions, government spending on welfare, and tax cuts) as nodes while modeling the associations between them as links, assuming that the constraint between two issues can be measured by the degree to which they are aligned in the mass public (Boutyline and Vaisey, 2017). Hence, BNA imposes a greater link strength among more highly correlated issue pairs.

Leveraging the network properties of belief system graphs, scholars have attempted to identify the central belief elements (Boutyline and Vaisey, 2017; Brandt et al., 2019) to examine how belief centrality may predict the change in the system (Fishman and Davis, 2022), and more pertinently to our present study, to explain the mechanism of polarization (DellaPosta, 2020). According to DellaPosta (2020), polarization can unfold both in the "heightening alignment across pairs of issues," and in the "broadening alignment across a wider range of issues." In BNA, these processes manifest through a rise in edge weights (i.e., increased correlation among issues), or an expansion in the size of connected components.

While inter-issue correlations can serve as indicators for the strength of dependency between variables, they cannot fully capture non-monotonic relationships where the change of one variable with regard to the other is not simply increasing or decreasing (Carpentras et al., 2024). Moreover, while BNA can capture the issue-wise alignment process, they do not explicitly encode ideologies (i.e., a coherent set of issue positions) as a spatial component of a belief network. Thus, we see an important gap between the theoretical framing of ideologies as the core product of (organized) belief systems (Converse, 1964), and the operational obscurity of how ideologies spatially manifest within a belief network. It is this gap that motivates our application of Response Item Networks (ResIN) to the analysis of ideological polarization within belief networks.

3. Data and methods

3.1 American national election studies (ANES)

The current study utilizes the American National Election Studies (ANES) from 2000 to 2020, a cross-sectional nationally representative survey of the general U.S population. We select six waves conducted in each presidential election year with a four-year interval. Using ResIN–a spatial belief network model described in further detail below–we create one snapshot for each wave to visualize the shifts in political beliefs throughout this period. In each snapshot, we include a set of politically relevant issues that were consistently assessed in all six waves of ANES (i.e., government service spending, government healthcare insurance, guaranteed jobs and income, aid to blacks, legal abortion), which allows for meaningful temporal comparisons. ANES respondents are asked to self-report their positions (i.e., attitudes) on these issues on either a 7 or 4 point scale. The complete set of issues is listed in Table 1, and Appendix A (ANES Included Items) provides the detailed issue descriptions and response options.

3.2 Creating resIN snapshots using ANES

While BNA uses individual nodes to represent a single issue (e.g. legalization of abortion), ResIN, instead, treats individual nodes as issue positions (e.g. the response "strongly agree" to legalization of abortion). Furthermore, as a "spatial network," each node in ResIN is located in an N-dimensional space, which can form the basis for a spatial model of ideology as an underlying left–right continuum. In what follows, we describe how we apply the main components of ResIN to the ANES data.[1] Readers should be advised that this procedure follows the exact steps as described in the work by Carpentras et al. (2024), which provides a comprehensive description of the method. In this article, we briefly walk through the main steps involved in ResIN-based analysis and focus on how this methodology can be used to explore the polarization dynamics in the belief system.

For a given issue selected from ANES, we first dummy code each issue position as a response variable. For instance, for the issue "guaranteed jobs and income," respondents indicate their attitudes via the response options ranging from 1 (i.e., "strongly agree; government should guarantee job and good standard of living") to 7 (i.e., "strongly disagree; government should let each person get ahead on their own"). For each response x from 1 to 7, we construct a set of binary variables `guar_jobs:x` indicating whether or not a given respondent has chosen response x (1 for yes, 0 for no). These binary variables are represented as nodes in ResIN. A positive[2] association between a given pair of binary variables from two different issues produces a weighted link between the corresponding two nodes. The link weight equals the strength of association, in this case, the phi correlation, which is an equivalent measure of the Pearson's correlation index for binary variables[3] (Carpentras et al., 2024). Intuitively, the correlation between two responses A and B is a measurement of how often people who select A also select B (and vice versa).

After setting up nodes and weighted links, we implement the force-directed layout algorithm (Fruchterman and Reingold, 1991), where node positions are determined by an equilibrium state that balances the attractive and repulsive forces among them (Carpentras et al., 2024). The greater the link weights between any two response node pairs, the more powerful the attractive force between them. This allows ResIN to visualize the network structure of political beliefs organically, placing nodes connected by stronger links closer to each other. We also use principal component analysis (PCA) to identify the main dimension among the obtained spatial coordinates among all nodes, which we align with the X-axis by rotating the initial solution. Thus, ResIN enables a spatial organization of attitudes (i.e., nodes) within a 2-dimensional plane, where the distribution of nodes along the (major) X-axis reflects their relative position along the most relevant latent variable. As we will later show in Section 4.1, the X-axis happens to align well with partisan identities, a node-level attribute that averages respondents' partisan identities. Carpentras et al. (2024) have shown that node positioning in ResIN is practically equivalent to latent variable modeling using Item Response Theory, in that distances between nodes represent corresponding distances in a latent space. Thanks to these unique features, ResIN is capable of identifying asymmetries in attitudinal patterns across the latent space of interest, as is shown in a recent application on vaccination attitudes (Carpentras et al. 2022).

To further assist in visualizing how node positions correlate with other covariates—such as party identity—we can use node color to indicate the average covariate value of all respondents who endorse the corresponding attitude in a given year. Here, we choose to color nodes based on partisan leaning, which, at the individual level, is measured by a Likert scale ranging from 1 (i.e., strong Democrat) to 7 (i.e., strong Republican) (see Appendix A Party Identification of Respondent). For instance, the color of the node `guar_jobs:1` in 2020 is determined by the average partisan leaning of all respondents who strongly believe that government should guarantee jobs and a good standard of living, according to their responses in 2020 ANES.

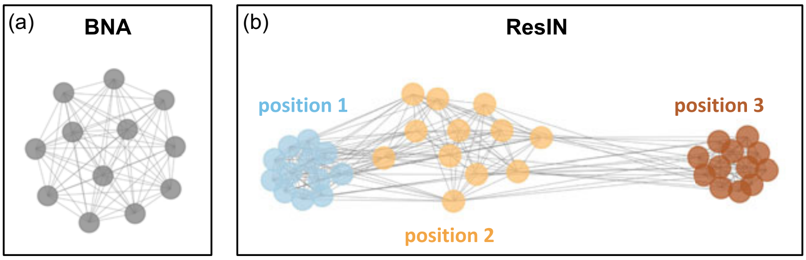

Figure 1. Comparison between BNA and ResIN on the same synthetic dataset. While BNA represents issues as nodes and association between issues as links, ResIN represents issue positions (i.e., attitudes) as nodes and association between issue positions as links.

Here, we provide a simple simulation to showcase ResIN's ability to spatially organize nodes in a 2-dimensional space, which is a key feature absent from classic BNA models. Figure 1 displays BNA and ResIN using the same synthetic data, where 1000 respondents self-report their positions on 12 issues via 3 possible response levels (i.e., agree, neutral, disagree). When all issues are correlated at similar levels, BNA displays a single connected component with no clear modular structure. In contrast, ResIN can reveal that responses corresponding to the same position are strongly connected (e.g., people who agree on one issue tend to agree on all other issues). Furthermore, we see that the neutral position (position 2) is closer to agree (position 1) than to disagree (position 3), which implies that people who remain neutral on some issues are more likely to agree rather than disagree on other issues. This simulated example shows how ResIN can reveal an asymmetric shape of a belief system that remains hidden in BNA.

3.3 Multi-level constraint and polarization measures afforded by resIN

Moving beyond revealing simple structural asymmetries within belief networks, we next discuss how ResIN can be used to study attitude structuration and polarization dynamics by offering quantitative, network-based polarization measures. In total, we propose five measures which operate at different levels: (i) two system-level measures that summarize the overall structuration and thus indicate the degree of constraint and polarization for an entire ResIN-network, and (ii) three attitude-level measures that articulate the specific role a given attitude plays in a (polarized) belief system.

3.3.1 System-level: How constrained and polarized is a given attitude space?

Based on Converse's definition of belief system constraint, we expect a highly constrained belief system to produce more interlocked issue positions, that is, more attitude pairs held together via stronger links. Therefore, an intuitive network metric to assess the system-level constraint is link density D, that is, the proportion of manifest links among all possible links within in a given network. Hence, let $G = (V, E, W)$ denote a ResIN with a set of nodes V, edges E and the corresponding edge weights W, produced by responses to a set of issues K, each with L_k possible response options. Thus, the numerator is the sum of link weights; and the denominator, the number of all possible links, equals the number of links that can connect nodes sourced from different issues. The link density of a given ResIN is therefore:

$$D = \frac{\sum_{e \in E} W_e}{\sum_{m \in K} L_m \left(\sum_{n \in K, n != m} L_n \right)}$$

Apart from computing D for the whole graph, we can also compute $D_{G'}$ for a partisan subgraph G' in a single ResIN. For instance, we can compute $D_{G_{rep}}$ for a subgraph G_{rep} consisting of only Republican-leaning nodes, that is, attitudes that are selected mainly by respondents who lean closer to Republicans.

Next, we introduce linearization as a measure of polarization, that is, the degree to which a network gets squeezed into a dominant latent ideological dimension (e.g., Stimson, 1975). In combination with force-directed layout algorithm, node positions in ResIN are determined by a varimax rotation that aligns the main orientation of the network with the X axis (i.e., the dominant latent ideological dimension). In this way, the spatial information of each node meaningfully indicates their position in a latent ideological space—a feature that we will demonstrate empirically in Section 4.1. In this space, a highly polarized belief system would flatten-out, or distribute linearly, such that knowing one's position along a single ideological dimension can well predict their positions on a variety of issues (we elaborate on this through simulation in Section 3.3.2). We leverage ResIN's spatial property and quantify the degree to which attitudes toward the five issues collapse into a single, dominant dimension, which can be visually grasped by the degree to which the nodes are being "squeezed" into a flat shape linear line. The linearization score E equals the ratio of X coordinates spread to Y coordinates spread for all nodes in a given ResIN network.

$$E = \frac{X_{max} - X_{min}}{Y_{max} - Y_{min}}$$

To assess the robustness of these system-level metrics, we conducted a subsampling-based sensitivity analysis by randomly re-sampling 80% of the yearly ANES data (without replacement). In each of 200 iterations, we regenerate the ResIN network, yielding a distribution of polarization scores for each year. Here, we report the interquartile ranges (IQRs) to show the degree of variability across subsampled results. We choose subsampling rather than classical bootstrapping, as duplicating responses from individual respondents–necessary in bootstrapping–may distort the network structure in ways that do not reflect realistic data variation. Furthermore, subsampling provides a more conservative estimate of robustness by testing how sensitive the polarization score is to partial data omissions.

3.3.2 Simulation of a "broken egg": the linearization process

Why is linearization a meaningful indicator of belief polarization? We answer this by observing how ResIN changes in shape as we move from a perfectly polarized system to a fully random one. To control the degree of polarization, we interpolate between a highly polarized model derived from Item Response Theory (IRT) (Samejima, 2011) and a random model that encodes no polarization. After more detailed model descriptions, we will explain why a highly polarized belief system yields a flat-shaped network and confirm a strong, monotonic association between polarization and linearization through simulation.

We use IRT to set up a polarized attitude system. Under the IRT paradigm, every respondent has (i) a value θ for a certain latent variable, and (ii) a so-called item characteristic curve $f(\theta)$ for every issue position. $f(\theta)$ determines the probability of this respondent selecting a certain issue position (Samejima, 2011). For instance, let us consider a case where the latent variable is the left–right spectrum and a small (large) value of θ indicates the left-wing (right-wing) position. For an issue position "support for gun control," because left-leaning respondents are more likely to support gun control in the U.S., we expect $f(\theta)$ to be greater for smaller θ (i.e. higher probability for left-leaning respondents to select this issue position), and smaller for larger θ. Usually, IRT-based probability curves have a bell-shape resembling normal distributions. For a given issue, if the peak of probability functions for issue positions are well separated (i.e., they overlap only minimally), people with similar values of θ would concentrate their responses on the same issue position, while people with different values of θ would have distinct issue positions. The random model, in contrast, supposes no latent variable nor any association between issue positions. For each respondent, it assumes that all possible positions are equally probable. Following the previous example,

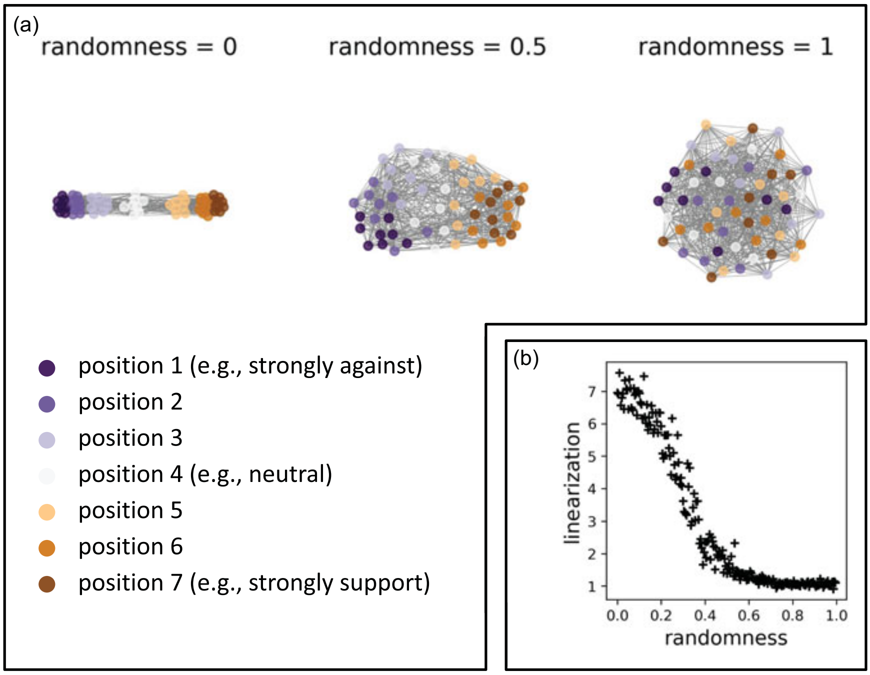

Figure 2. "Broken egg" simulations with varying randomness parameters r. Subfigure (a) shows the ResIN output generated by $r = 0, 0.5, 1$; subfigure (b) shows the negative relationship between randomness and linearization level.

within the random model, a right-leaning respondent is equally likely to select any position for a given issue, regardless of the ideological characteristics of the position. One simple implementation of this model is given by setting all item characteristic curves to be constant and identical one another.

To control the level of polarization, we interpolate between a well-polarized IRT model and the random model using a "randomness" parameter r. Therefore, the final item characteristic curve for a given r is:

$$f_r(\theta) = (1 - r)f(\theta) + r/L$$

where $f(\theta)$ is the "classic" item characteristic curve, as obtained from Samejima (2011), and L is the number of issue positions for a certain issue (e.g., corresponding to the number of response options in a survey). In each simulation round, we fix the number of respondents ($N = 1000$), the number of issues ($K = 8$) and the number of positions per issue ($L = 7$), and vary the randomness parameter r. Each respondents has a random value for the latent variable θ. Based on the issue position probability computed via $f_r(\theta)$, each respondent selects one position from each of the 8 issues. In this manner, we are able to generate synthetic datasets resembling survey responses. From here, we repeat the same procedure generating ResINs and measure linearization for each simulated network.

We display the simulation results in Figure 2. Panel (a) displays three ResIN snapshots obtained from $r = 0$, 0.5, and 1 and panel (b) shows the monotonically negative relationship between r and linearization. When the system is fully polarized (i.e., $r = 0$), the corresponding network is stretched flat and fully elongated, exhibiting a high level of linearization. As we increase the noise by tuning up the randomness parameter, the elongated structure folds on itself and starts to take a more oval shape, and the linearization level drops rapidly. Finally, in the case of pure randomness when $r = 1$ and all issue positions are equally probable,[4] the system displays a round shape with a linearization level approximating 1.

Why, one may wonder, does ResIN change its shape in response to variations in belief system polarization? And more precisely, why would an increase in polarization bring forward a "broken-egg" process in ResIN? Remember that proximity between nodes (i.e., issue positions) in ResIN indicates a high degree of attitude co-endorsement. Given the structure of IRT, issue positions with similar mean value in their item characteristic curves are likely to be co-selected by the same people, and thus tend to form clusters in ResIN. Within a structured IRT model (i.e., a polarized belief system), the item characteristic curves are well sorted along the natural order of issue positions, such that respondents with the same θ value are most likely to select the same position, fairly likely to select adjacent positions, but less likely to select more distant positions. For instance, consider three positions (i.e., support, neutral, and against) toward gun control. A structured IRT would predict left-leaning respondents to most likely to choose "support," moderately likely to choose "neutral," and least likely to choose the "against" option. The inverse would be true for right-leaning respondents. Meanwhile, centrist respondents would most likely be neutral toward gun control, and less likely to support or be against gun control. A belief system with multiple issues resembling this very item response structure would naturally lead to a ResIN solution in which the neutral positions are connected to the support and against positions, yet the support and against positions are only weakly connected. A force-directed layout balancing the attractive and repulsive patterns would thus result in a linearized, left–right attitude structure indicative of a highly polarized system.

To sum up, the present simulations help us understand how and why the shape of ResIN-networks is indicative of belief polarization along a latent ideological dimension. A weakly polarized belief systems produces an unstructured cloud-like ResIN, while a strongly polarized belief system produces a linear-shape ResIN that map issue positions closely along a single dimension.

3.3.3 Attitude-level: How (de-)polarizing are certain attitudes?

Next we analyze ResIN at the node level. Our main aim here is to reveal heterogeneity in the structural function of different attitude nodes within ResINs. More particular, we are interested in identifying (a) ideological centroids, that is, nodes at the center of divided ideological communities and (b) attitudinal bridge(s), that is, nodes that could help bridge distinct ideological camps.

To accomplish the former, we focus on the node strength centrality as a measure of local importance. Previous research relying on classic BNA models claims that nodes higher in strength are more central to people's belief systems (Boutyline and Vaisey, 2017; Brandt et al., 2019; Warncke, 2025). Leveraging ResIN, we can extend this approach to within-cluster analysis, investigating which issues are relatively more important to Democrats rather than Republicans. Purportedly, these issue positions should also be the most polarizing to the opposite ideological camp.

Now, we turn toward attitudinal bridges. To illustrate how we find issue positions with the most de-polarizing potential, let us consider a scenario featuring two completely sorted issues (i.e., A, B; Figure 3a), where knowing one's position on issue A can give full information on their position on issue B (e.g., people who choose position 1 for A, i.e., A_1, would definitely choose position 1 for B, i.e., B_1). Here, two respondents either agree completely on both issues or share no common position at all. However, if a comparable number of respondents who select A_1 and B_1, and those who select A_3 and B_3, can agree on another issue C (e.g., if they have all selected C_3), it would be possible to bridge the debate through finding a common ground on C. In this case, response C_3 would thus function as an attitudinal bridge. In Figure 3b, we highlight six such attitude bridges through which respondents can establish partial agreement on one issue while disagreeing on the other(s). Using ResIN, we can measure such bridging power by computing the node-level betweenness centrality, a measure counting how many times a node lies on

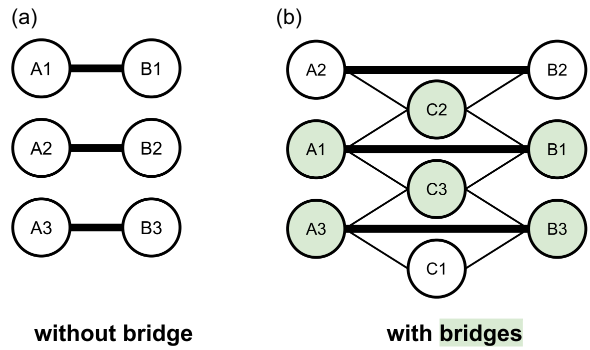

Figure 3. Illustration of a toy ResIN model with two issues (a) and three issues (b). Each issue has three positions. The left panel (a) demonstrates the scenario where the population perfectly sorted along issue *A* and *B*, and there is no bridge connecting mismatched positions such as A_1 and B_3. The right panel (b) shows a scenario where some positions along issue *C* serve as bridges connecting previously isolated attitudes; similarly positions along *A* and *B* can also serve as bridges for *B*-*C* and *A*-*C*. The green color highlight those bridge attitudes.

the shortest path between any pair of nodes[5] (Freeman, 1977). Nodes that are frequently on the shortest paths connecting two or more ideological communities are more likely to serve as the common ground, thus likely showing the highest de-polarization potential in cross-community engagement. Alternatively, we also compute closeness centrality, which is the weighted inverse of the total shortest-path distance from a node to every other reachable node and hence represents a quantitative measure of global connectedness of a given attitude. Conceptually, a high betweenness and closeness centrality should be jointly indicative of node-level bridging power in a belief system.

4. Results and discussion

In this section, we first present BNA and ResIN belief networks for the ANES 2000–2020 before discussing the insights we can glean from each. We show that ResIN represents spatial node positions that reflect meaningful ideological differences. BNA solutions, however, do not offer a comparable method of spatial node positioning. Second, we use system-level constraint and polarization measures (i.e., link density and linearization) to summarize the overall trend of polarization over time. Third, our analysis of the ANES 2020 data focuses on more details of our attitude-level metrics, allowing us to discuss the varying roles of particular response nodes in constraining different partisan groups while contributing to system-level (de-)polarization within belief networks.

4.1 Meaningful spatial organization of Democratic/Republican crowd

We start with ResIN's capability to visualize the spatial clustering of co-endorsed issue positions. Figures 4 and 5 display the BNA and ResIN snapshots of political belief system modeled based on the same six waves of ANES data from 2000 to 2020.

BNA captures belief constraint through bivariate correlations among the issue-level responses. The top pane of 4 thus illustrates the overall trend of increasing constraint among the five issues while showing how abortion has evolved from a weakly constrained issue at the periphery of the system, into a well integrated component. In Figure 4, we also correlate issue responses with the average partisan leaning and color nodes based on the correlation strength. While BNA-based visualizations could reveal how issue positions are increasingly sorted with partisan leanings over

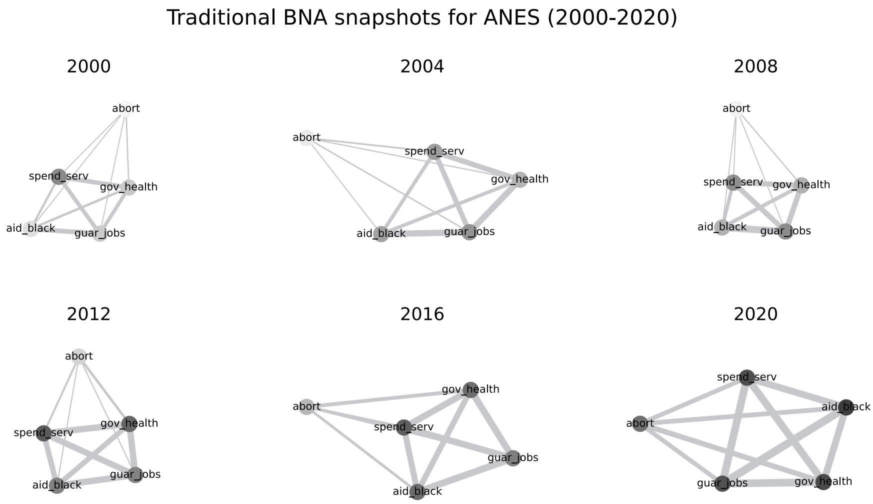

Figure 4. Traditional BNA snapshots of ANES data from 2000 to 2020, every four years in the presidential election cycle. Each node represents a single issue (e.g., `spend_serv` represents the issue regarding increase or decrease government's service spending). The edge width is a function of weights, indicating the absolute correlation strength between two corresponding issues. The node color is a function of the absolute correlation between the average partisan leaning and positions toward the given issue. Node positions are determined using the force-directed layout algorithm to ensure a fair comparison between BNA and ResIN.

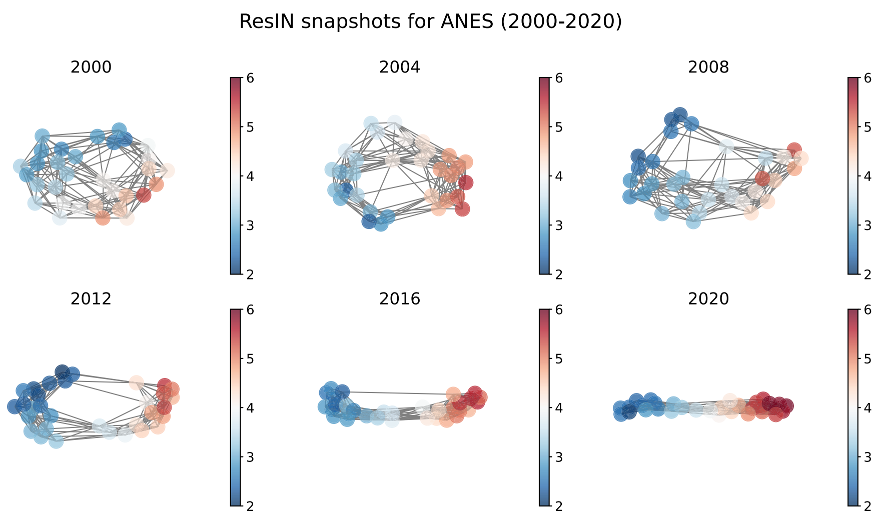

Figure 5. ResIN snapshots of ANES data from 2000 to 2020, every four years in the presidential election cycle. Each node represents a specific attitude toward a given issue (e.g., `abort:1.0` represents the attitude "abortion should never be permitted" and `abort:4.0` represents "abortion should never be forbidden"); the link strength between two nodes reveals the extent to which those who choose or did not select these two attitudes overlap. Node color indicates the 7 point scale partisan leaning averaged at the node level; 7 (1) means the attitude is selected only by strong republicans (strong democrats). Node positions are determined by the force-directed algorithm that pulls strongly linked nodes closer and a final rotation that aligns the main dimension of the network with X-axis.

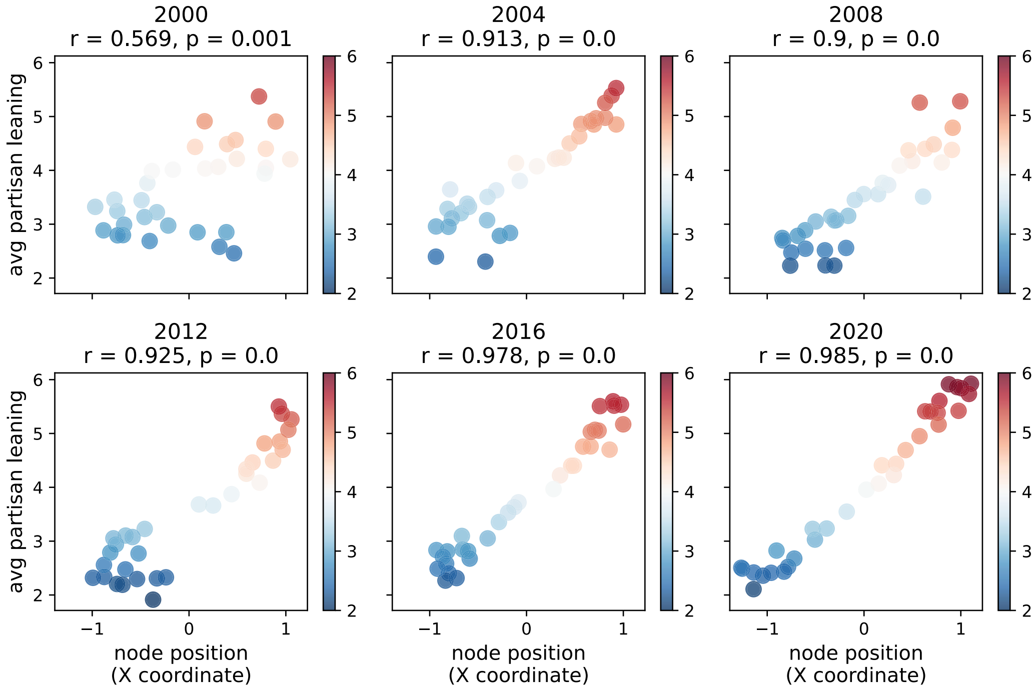

Figure 6. The correlation between X coordinates and average partisan leaning at the node level.

the past two decades, they are unable to capture the increasingly spatial polarization of the attitude space. Because different positions towards a certain issue are collapsed to a single node, BNA is not designed to map beliefs based on their relative positions in an intuitive and theoretically meaningful latent space.

In contrast, ResIN paints a richer and more granular picture of the polarization process. Overall, the evolution of the belief system resembles the breaking of an egg: starting from a very diffuse attitude "blob" in 2000, with mixed endorsements from Republicans and Democrats on many issue positions, the belief system gradually develops a more modular structure with a clear division between Republican and Democratic attitudes. The overall shape of the attitude space, meanwhile, becomes gradually more linear as different attitudes toward policy issues increasingly experience alignment with the dominant Republican-Democratic divide. This development largely resembles the simulation results from the least to the most polarized attitude systems discussed in Section 3.3.2.

Moreover, the X coordinate of each node in each ResIN snapshot corresponds reasonably well with the average partisan leaning (see Figure 6). This suggests that the X coordinate can be interpreted as a latent variable (as shown in Carpentras et al. (2024)) which in our this corresponds to the latent ideological position of each attitude. We would like to stress that ResIN is able to organically reconstructs the main ideological divide without any prior knowledge about the ideological implications of issue positions in the U.S.

In sum, ResIN not only retains the BNA feature of displaying belief constraint, but also captures how the increase in ideological polarization occurs together with the enhance in alignment of issue positions with partisan identities. By moving the analysis to the attitude level, ResIN provides a more detailed picture of evolving belief constraint, polarization, and partisan sorting than issue-level BNA models, while uncovering spatially meaningful organization along latent political ideology.

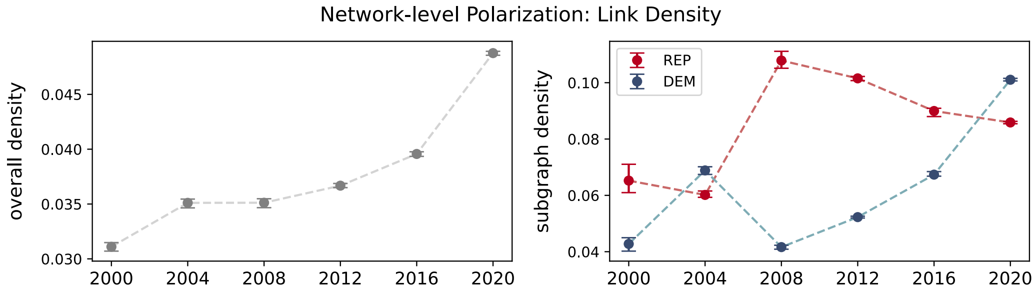

Figure 7. System-level polarization measures: link density over years for the entire network (left) and for partisan subgraphs (right). The errorbars show the interquartile ranges (IQRs) of metrics produced by 200 rounds of re-sampling, each taking 80% of the survey responses.

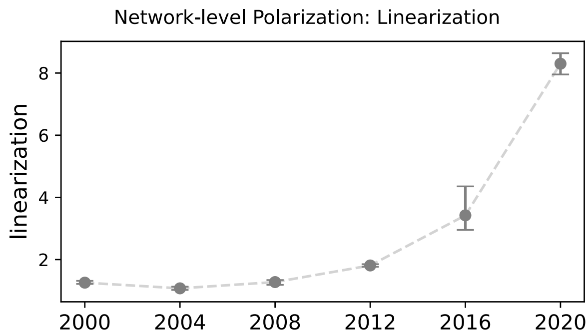

Figure 8. System-level polarization measure: linearization over years for the entire network. The errorbars show the interquartile ranges (IQRs) of metrics produced by 200 rounds of re-sampling, each taking 80% of the survey responses.

4.2 System-level analysis: ideologically distant, and sorted partisans

We now turn to the quantitative results of system-level constraint and polarization. Using two metrics—link density and linearization—we discuss the overall belief structuration trends among U.S. political beliefs between 2000 and 2020 in this section.

Figure 7 shows the results of link density, both for the entire network (left) and for Republican and Democratic subgraphs[6] (right). We note that constraint has been steadily rising over the past two decades, as the link density has increased by 51.1% from 0.032 to 0.049. Following a period of relatively mild increases from 2004 to 2016, the public saw its most rapid episode of rising constraint between 2016 and 2020. This trend, however, did not unfold symmetrically across partisan groups. As shown in the right subfigure, the Democratic and Republican subgraphs have undergone quite distinct trajectories. Compared to its Republican counterpart, the Democratic subgraph generally showed a lower link density, with the exception of 2020. From 2000 to 2020, the Democratic side reached its first local peak in 2004, bounced back to a low level in 2008 and has been consistently growing since then. Subgraph density among Republicans peaked out early on in 2008, with the density level continuously declining from 2008 to 2020. These differences in belief constraint between Democrats and Republicans appear to have roots in an interesting partisan asymmetry that should be further investigated in follow-up research.

In terms of linearization, the result delivers a fairly similar message: while the overall belief system has become more polarized from 2000 to 2020, the most dramatic shift occurs between 2016 and 2020 (see Figure 8). Beyond attitudes simply forming stronger interlocking structures (which results in a higher link density), our analysis shows that the system is also becoming increasingly well-sorted along a dominant ideological axis. The rising degree of polarization is not driven by some random new ties between attitudes, but by a more systematic sorting that arrange issue positions along the ideological dimension into a consistent, liberal-conservative orientation.

4.3 Attitude-level analysis: centroids and bridges in a polarized belief system

Delving deeper into the micro-structure of attitude networks, ResIN further enables investigations at the node-level, including details on how much a given attitude is contributing to aggregate polarization dynamics. Mirroring existing work using BNA literature, ResIN can uncover that different political beliefs perform different roles in structuring mass a belief system. A classic yet still prominent argument, for instance, holds that some beliefs are more central and thus exert a greater structural influence over others (Converse, 1964). A number of recent works have successfully leveraged node-level centrality metrics, such as *strength*, *betweenness*, and *closeness*, to test claims the relative importance of individual nodes to the structural cohesion of belief systems at large (Boutyline and Vaisey, 2017; Brandt et al., 2019; Warncke, 2025).

While insightful, *strength*, *betweenness*, and *closeness* arguably capture a very similar phenomenon, that might be labeled general attitude centrality in classic BNA models (see Brandt et al. (2019)). However, these quantities allow us to discriminate fundamentally different structural roles in ResIN. As opposed to its corresponding interpretation in BNA, high *strength* centrality denotes local importance to a particular belief sub-cluster. A comparison of node strength centrality in ResIN can, therefore, be indicative of the relative importance of different attitudes to different partisan-ideological communities. As seen in the second panel of Figure 9, defending abortion rights is a much more central attitude to Democrats while the most central issues for Republicans deal with government sponsored healthcare and federal job guarantees. These results cannot easily be obtained using classic BNA (see the top panel in Figure 9), which would simply locate the guaranteed jobs issue as the most central overall, remaining oblivious to the possibility that different attitudes can be more or less central to different ideological communities.

One peculiar feature inherent in BNA is that strength and closeness centrality are equivalent for networks in which all shortest network paths are direct paths. In this case, betweenness centrality remains constant at zero across all nodes. Figure 9 shows that this is indeed the case if we apply BNA to the ANES 2020 case. In ResIN, however, closeness and betweenness centrality not only indicate different belief system functions, but they are also largely decoupled from metric equivalencies with strength centrality.

Gleaning at the third panel in Figure 9, we note that nodes with high betweenness and closeness centrality tend to lie in between the Democrats and Republican clusters. These attitudes are typically moderate in nature and tend to be more frequently endorsed by Independents. According to our model in the bottom panel of Figure 9, if one would like to find the most likely issue position providing common ground between Democrats and Republicans, the best bet would be to establish conversations about the general state of public services and about government healthcare. In contrast, one should avoid issues concerning abortion and race.

Then, how stable are the above referenced node-level metrics across time? Do Democrats and Republicans consistently prioritize different issues or was there once more common ground between them? Figure 10 summarizes the relative strength centrality estimates within the Democratic and Republican clusters over the past 20 years. Again, we assign each response node to either partisan camp based on whether more Democrats or more Republicans, on average, endorsed the given item response.[7] Focusing on relative within-cluster strength centrality statistics, we notice that while both partisan groups consistently possess attitudes about government health insurance and job guarantees at the center of their attitude clusters over the past 20 years, there were also marked and evolving variations throughout this process. Whereas

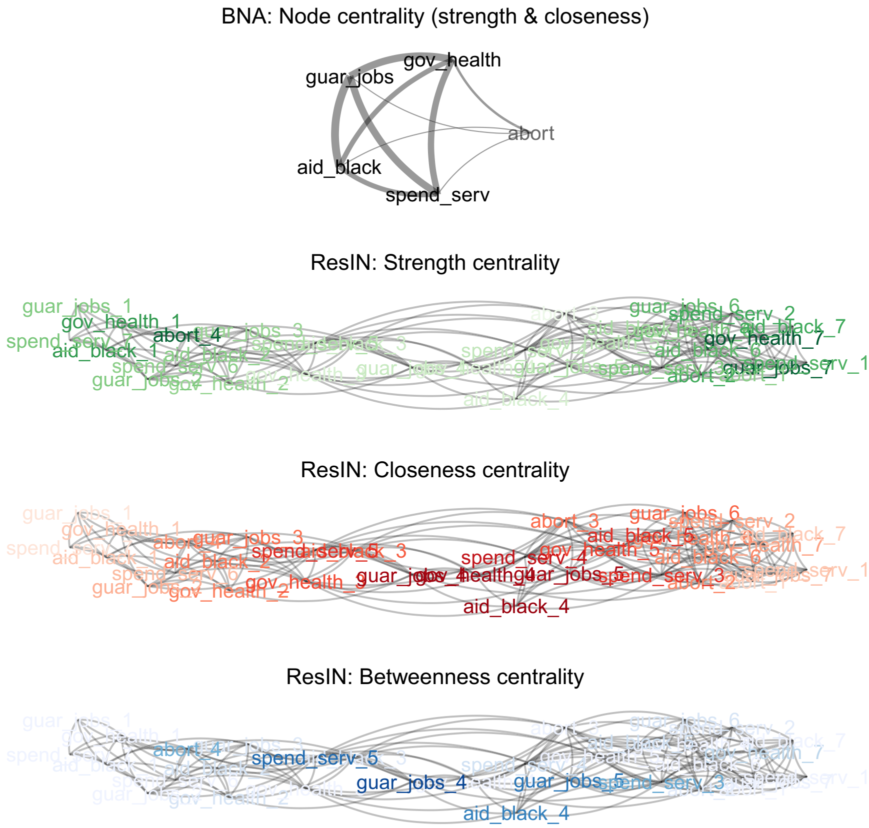

Figure 9. Node centrality statistics in BNA and ResIN using the same ANES 2020 data. Color intensity denotes more central nodes. Based on strength and closeness centrality, the most central nodes in the BNA model are government health insurance (0.138), guaranteed jobs (0.137), aid to African Americans (0.132), government service-spending (0.131), followed by legal access to abortion (0.11). Note that strength and closeness centrality are equivalent in BNA (but not in ResIN) as all closest network paths are direct paths.

abortion attitudes featured among the least important to early 2000's Democrats, their importance in structuring the remainder of their attitude cluster has steadily risen, until becoming the most central attitude in 2020 (i.e., by substantial margins). During the same period, aid to African Americans almost entirely lost its once central position within the liberal attitude cluster. Among the Republican community, meanwhile, abortion attitudes never played a pivotal role as an ideological anchor in any of the measured years.

In Figure 11, we map the evolution of node closeness and betweenness centrality across time. While both quantities generally point to similar nodes as providers of attitudinal bridges between partisan communities within each year, we notice a general trend in falling closeness but growing betweenness centrality estimates as time progresses. This trend appears to be bourne out of the attitude polarization process captured in the ResIN-networks depicted in Figure 5: as cross-partisan edges disappear and the system linearizes, fewer and fewer attitudes provide effective communicative bridges between partisan camps. This makes the few remaining linking nodes ever more vital, as signified by growing absolute betweenness centrality statistics of nodes, particularly in the upper right corner in Figure 11's lower pane. These nodes, which generally represent issue positions mildly in favor of greater re-distribution and government intervention in the economy, appear most likely to equally appeal to both partisan camps.

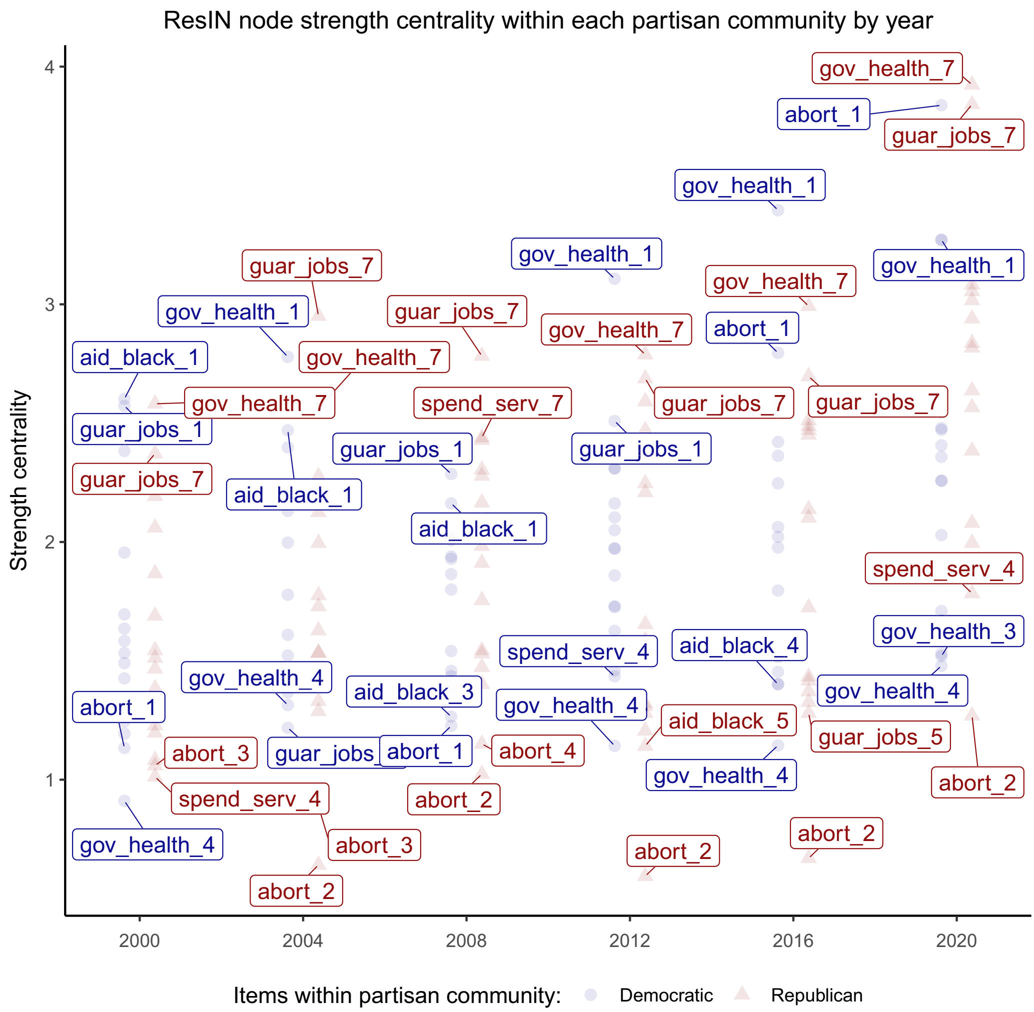

Figure 10. ResIN node strength centrality statistics within each partisan sub-cluster and presidential election year. For clarity, we only labeled the top, runner-up, and bottom two attitude nodes within each cluster. Clusters memberships were assigned based on whether more Democrats or more Republicans endorsed a particular issue position in a given year. Source: ANES cumulative file.

5. Limitations and future research

While our study adds valuable insights to the field of BNA and belief system structuration, it has important limitations. First, both the structure of ResIN and the derived polarization measures depend on the selection of issue items. In this study, we carefully select political issues that we assume to be salient and relevant; however, our choices are limited by data availability. Although all analyses depend on the selected data, future research could evaluate the generalizability of ResIN with different issue selections.

Second, since the ResIN-based polarization measures we propose are novel, there is much left to explore beyond our current analyses. This includes testing their unique predictive power for different forms of attitude structuration processes—such as belief constraint and polarization—as well as assessing their performance on other datasets or through simulations. We hope our findings will encourage researchers to further investigate these proposed measures in the future.

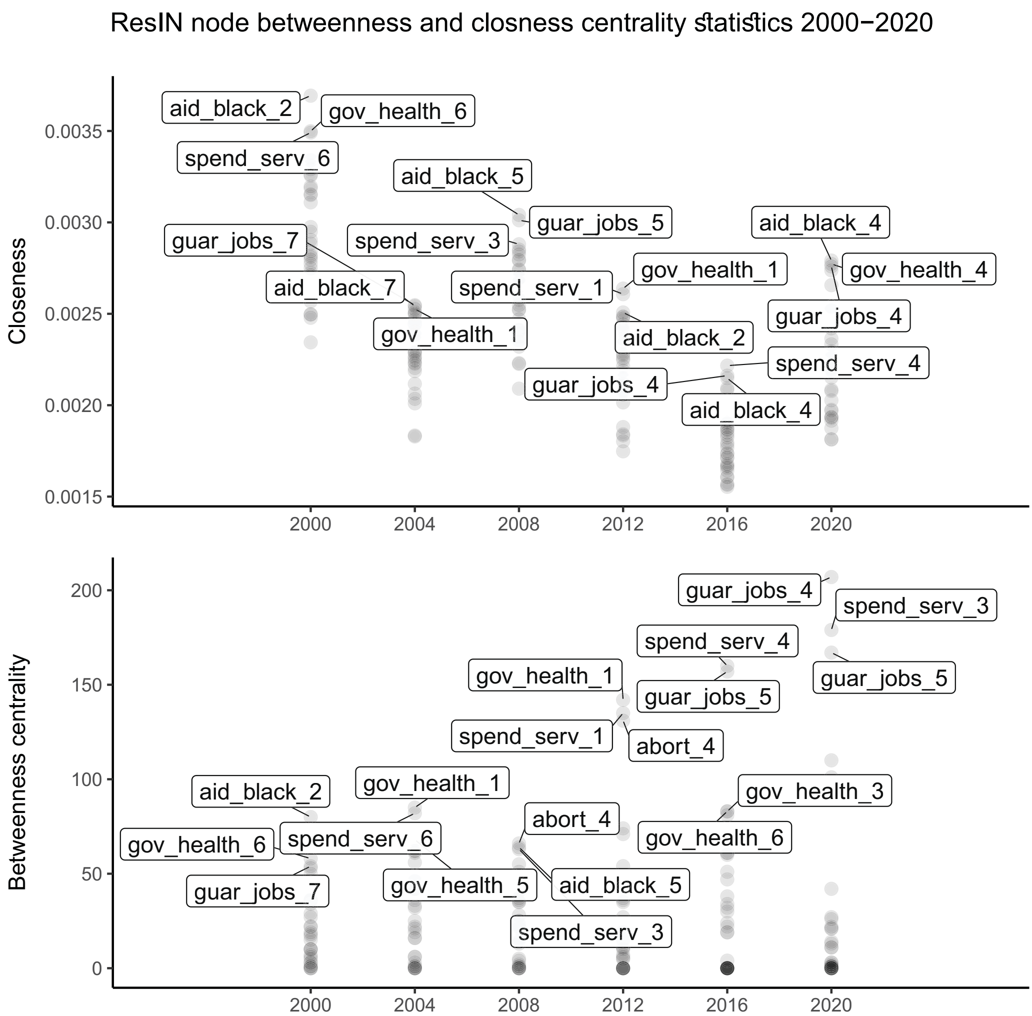

Figure 11. ResIN node closeness and betweenness centrality statistics for each presidential election year. Only labeled the top three nodes based are labeled based on each centrality statistic. Source: ANES cumulative file.

Third, although we have demonstrated that ResIN provides novel insights into polarization in the U.S., our model still needs to be tested and validated in comparative contexts. While other work has applied ResIN across European countries using European Social Survey (ESS) and showcased the varying structural properties of European belief systems (Warncke et al., 2025; Van Noord et al., 2025), the current analysis on the case study on ANES may not be directly applicable in scenarios where the belief system remain largely unstructured. Moreover, the two-dimensional space used in our visualizations may be sufficient to describe the structure of belief networks in a two-party system, but it may oversimplify the ideological space in other contexts where belief networks might follow a higher-dimensional structure. Although ResIN is capable of capturing multidimensional belief networks, it may lose detail when being projected onto a low-dimensional latent space. Therefore, the extent to which ResIN can offer similar insights in cases where belief networks are higher-dimensional remains uncertain and should be explored through further research applying ResIN to other datasets and contexts.

6. Conclusion

Recent BNA research has shown that studying ideological polarization from a network perspective is both promising and insightful. However, BNA is not able to map a belief system within an interpretable, latent ideological space. ResIN—a novel belief network model operating at the item response level, shows high promises for addressing this limitation. In this paper, we therefore advocate for the usage of ResIN in the study of ideological polarization and demonstrate its ability to reveal additional information hidden in classic BNA models.

By analyzing five issues across six waves of ANES data from 2000 to 2020, we find that the ResIN well captures the recent polarization process of political beliefs in the U.S. public which resemble the "breaking of an egg." Using two system-level measures, we assess the degree of belief system constraint and polarization, showing an overall trend of increasing ideological polarization over the two-decade period, with the most dramatic rise occurring between 2016 and 2020. In addition, we identify an intriguing partisan asymmetry in belief system constraint, with Democrats' belief systems generally appearing less coherent than that of Republicans during this period—a pattern that only recently reversed in 2020. At the attitude level, we identify the different roles that particular attitudes played in the structure of different belief network communities. For instance, abortion appeared as the most central issue for Democrats but not Republicans; government spending on public services and healthcare was one common ground for bridging both of the otherwise highly polarized partisan communities.

In sum, the present study shows that ResIN is a promising tool to assess the state and process of polarization, as demonstrated by our simulations and the empirical examples using ANES data. ResIN goes beyond the information provided by BNA, as it intuitively visualizes ideological alignment throughout polarization processes and provides quantitative measures for these dynamics at the system and attitude level.

Acknowledgments. This study is an extended project from the Computational Social Science Summer Schools held at Bremen International Graduate School of Social Sciences (BIGSSS), Germany, July 3–23, 2023.

Competing interest. The authors declare no competing interest.

Funding statement. DC is grateful for the support by the project "CoCi: Co-Evolving City Life" funded by European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program, grant agreement No. 833168. BB is grateful for the support of the FAST project funded by ERC under grant agreement No. 101044076. PW is grateful that this work has been supported by the ERC grant "ID-COMPRESSION" with number 101124175, funded in part by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

Data and code availability statement. The study uses public datasets retrievable from American National Election Studies (ANES). The code for analysis can be found in the repository: github.com/yijingch/broken-egg-polarization.

Notes

1 A full description of ResIN and its properties is beyond the scope of this article but we encourage interested readers to refer to Carpentras et al. (2024) and Lüders et al. (2024).

2 Negative edges are excluded from the visualization to avoid visual clutter and because previous research (Carpentras et al., 2024) has shown that the positive edges contains already enough information for studying the network structure. Furthermore, many useful visualization algorithms or analysis methods cannot handle negative edges (e.g., force-directed algorithms).

3 Please note that phi correlation, Pearson correlation, and Spearman correlation are identical for binary variables (Guilford, 1941).

4 Ideally, this will result in all issue positions having 0 correlation to each other, but, due to the finite number of people, correlations are not exactly 0, but present some random deviation from it. As a result, every issue position is connected to other random positions, resulting in the circular pattern that we observe in the figure.
5 Because ResIN assign link weights based on attitude associations, attitudes with a greater association are thus connected with stronger links and pulled closer, which means node distances would decrease as link weights increase. Hence, we use the inverse of link weight to attribute edges in the calculation of shortest path length.
6 As mentioned in Section 3.3.1, the Republican (Democratic) subgraph refers to a subset of ResIN consisting of nodes representing attitudes endorsed primarily by respondents who lean toward Republicans (Democrats).
7 Note that ResIN offers other clustering options as well; see Warnckeet al. (2024).

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Appendix A: ANES included items

Party identification of respondent

(VCF0301) Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or what?

1. Strong Democrat
2. Weak Democrat
3. Independent – Democrat
4. Independent – Independent
5. Independent – Republican
6. Weak Republican
7. Strong Republican

Attitudes regarding five issues

Table 1. Selected issues from ANES to include in ResIN

ANES code	Abbreviation	Description	Levels of attitudes
VCF0839	spend_serv	Government service-spending scale	7
VCF0806	gov_health	Government health insurance scale	7
VCF0809	guar_jobs	Guaranteed jobs and income scale	7
VCF0830	aid_black	Aid to black scale	7
VCF0838	abort	By law, when should abortion be allowed	4

Government service-spending scale
Some people think the government should provide fewer services, even in areas such as health and education, in order to reduce spending. Suppose these people are at one end of a scale, at point 1. Other people feel that it is important for the government to provide many more services even if it means an increase in spending. Suppose these people are at the other end, at point 7. And of course, some other people have opinions somewhere in between, at points 2, 3, 4, 5, or 6. Where would you place yourself on this scale, or haven't you thought much about this?

Government health insurance scale
There is much concern about the rapid rise in medical and hospital costs. Some people feel there should be a government insurance plan which would cover all medical and hospital expenses for everyone. Suppose these people are at one end of a scale, at point 1. Others feel that medical expenses should be paid by individuals, and through private insurance plans like Blue Cross. Suppose these people are at the other end, at point 7. And of course, some people have opinions somewhere in between at points 2, 3, 4, 5 or 6. Where would you place yourself on this scale, or haven't you thought much about this?

Guaranteed jobs and income scale
Some people feel that the government in Washington should see to it that every person has a job and a good standard of living. Suppose these people are at one end of a scale, at point 1. Others think the government should just let each person get ahead on his/their own. Suppose these people are at the other end, at point 7. And of course, some other people have opinions somewhere in between, at pints 2, 3, 4, 5 or 6. Where would you place yourself on this scale, or haven't you thought much about this?

Aid to black scale
Some people feel that the government in Washington should make every effort to improve the social and economic position of blacks. Suppose these people are at one end of a scale, at point 1. Others feel that the government should not make any special effort to help blacks because they should help themselves. Suppose these people are at the other end, at point 7. And of course, some other people have opinions somewhere in between, at points 2, 3, 4, 5 or 6. Where would you place yourself on this scale, or haven't you thought much about it?

Legal abortion scale
There has been some discussion about abortion during recent years. Which one of the opinions on this page best agrees with your view? You can just tell me the number of the opinion you choose.

1. By law, abortion should never be permitted.
2. The law should permit abortion only in case of rape, incest, or when the woman's life is in danger.
3. The law should permit abortion for reasons other than rape, incest, or danger to the woman's life, but only after the need for the abortion has been clearly established.
4. By law, a woman should always be able to obtain an abortion as a matter of personal choice.

Cite this article: Chen Y., Speer A., de Bruin B., Carpentras D. and Warncke P. (2025). A "broken egg" of U.S. Political Beliefs: Using response-item networks (ResIN) to measure ideological polarization. *Network Science* **13**, 1–22. https://doi.org/10.1017/nws.2025.10016