# **I. Title:** Network Analysis of Attitudes Towards Inequality: Estimating the Impact of Anger and Simulating Attitude Change

# II. Abstract and keywords

This article explores the growing field of subjective inequality, addressing limitations of prior social justice research, which often employed unsystematic approaches or focused narrowly on population-level attitudes. Using a tripartite analytical strategy on ISSP data from the U.S., we first *model* attitudes towards economic inequality as a belief system, which is a small-world network of interacting cognitive evaluations. Support for public redistribution and perception of income inequality are the most central attitudes. Additionally, we *estimate* how anger towards inequality impacts this belief system, using a moderated network model to demonstrate that anger significantly affects nearly one-third of the network’s ties. Lastly, by *simulating* changes in attitude, we find that modifications at the network’s central nodes are particularly relevant, as they lead to significant overall shifts in the belief system. This comprehensive approach provides a nuanced view of the complex dynamics of public opinion on inequality, its structure and its change.

Keywords: Attitude network; Belief systems; Attitudes towards inequality; Social justice research.

# III. Main text

## 1. Introduction

Inequality is one of the most pressing challenges in contemporary societies, particularly in the United States, where economic disparities are among the highest in Western nations (Atkinson et al., 2011; Neckerman & Torche, 2007). Over recent decades, rising disparities have created significant gaps in living conditions (Wilkinson & Pickett, 2009), with the richest 10% controlling about 70% of wealth while the bottom half owns less than 2% (Chancel et al., 2022). These issues are exacerbated by strong socioeconomic segregation (Mijs & Roe, 2021) and limited social mobility (Hout, 2018; OECD, 2018). Despite these economic gaps, public concern about inequality has not risen proportionately (Kenworthy & McCall, 2007; Lierse et al., 2022), with individuals often misunderstanding or underestimating its extent (Chambers et al., 2014; Trump, 2023). The U.S. is an especially relevant context for studying attitudes toward inequality due to its deep disparities and a long tradition of research in this field (e.g., Kluegel & Smith, 1981; McCall, 2013). Prior studies highlight the U.S. public’s strong belief in meritocracy (Mijs, 2018b) and relatively low support for redistribution (Alesina et al., 2001; Hoy & Mager, 2021) (Alesina et al., 2001; Hoy & Mager, 2021).

Research on distributive justice has traditionally relied on the latent variable approach, which consolidates multiple perceptions, beliefs, and judgments into mean indexes. This approach often leads to an unsystematic examination of these attitudes, with most studies focusing on only one aspect (Janmaat, 2013).  Moreover, research has primarily focused on the levels of these attitudes (i.e., their public endorsement), often overlooking the cognitive structure in which they are embedded. This is crucial because attitudes do not exist in isolation but are interconnected within a broader belief system (Converse, 2006). Recent interdisciplinary research has provided innovative methodologies for analyzing the multifaceted components of attitudes towards inequality and understanding their structural organization. A new scholarship in distributive justice indicates that these attitudes form inequality belief systems, which are mental structures composed of nodes representing survey variables and ties representing their statistical associations in the data (Bertero et al., 2024; Franetovic & Bertero, 2023). Further, research has revealed that the structure of attitudes towards inequality varies across different social strata (DiMaggio & Goldberg, 2018; Franetovic & Bertero, 2023; Hunzaker & Valentino, 2019). These inquiries complement latent variable approaches by shifting the focus from individuals’ normative views on inequality to understanding how these stances are organized within broader mental structures (Brandt & Sleegers, 2021; Dalege et al., 2016).

The network approach to studying attitudes towards inequality has two major limitations. First, researchers often split samples into groups to examine belief systems, either by grouping individuals with similar attitudinal structures (DiMaggio & Goldberg, 2018; Hunzaker & Valentino, 2019; Kesberg et al., 2024) or by comparing the belief systems of individuals with different socio-demographic characteristics (Franetovic & Bertero, 2023; Schlicht-Schmälzle et al., 2018). While useful, this reduces statistical power and assumes belief systems differ only between groups, ignoring variations within them. Second, studies rarely examine attitude change, overlooking Converse’s (2006) key proposition that shifts in one belief can realign others. For instance, heightened awareness of income inequality might lead to stronger support for redistributive policies, yet this dynamic remains largely unexplored (Brandt & Sleegers, 2021).

We craft a tripartite analytical strategy to address the limitations in the study of inequality belief systems. First, we *model* U.S. attitudes toward inequality as a belief system using ISSP data, creating a weighted and signed network that captures the relationships between perceptions, beliefs, and judgments of inequality. Second, we *estimate* how this structure varies across the population, focusing on the role of anger towards inequality. By applying a Moderated Network Model, we show that angry individuals possess more interconnected and polarized belief system structures. Finally, we *simulate* attitude change to investigate whether altering central nodes leads to broader adjustments within the belief system.

Our contribution is structured as follows. Section 2 introduces the concept of attitudes toward inequality and reviews network approaches to address their structure. Section 3 details the ISSP data and methods used. Section 4 confirms that U.S. attitudes form a small-world inequality belief system centered on public redistribution and income inequality, with significant variations based on anger levels. We also show that changes in central beliefs drive substantial system-wide adaptations. The study concludes with a discussion of its methodological and theoretical contributions and directions for future research.

## 2. Theory

### 2.1 Attitudes towards inequality

Attitudes are “general evaluations that people hold regarding a particular entity, such as an object, an issue, or a person” (Lavrakas & J., 2008; p.39). Attitudes are thus evaluative since they represent positive or negative judgments; they are general, meaning that even a complex attitude object can usually be associated with an overall attitude construct; they are also targeted and—at least partially—enduring, being more restricted than moods and general dispositions, and less volatile than rapid impressions (ibid.). In social sciences, attitudes are studied because they strongly predict relevant social and political behaviors (Hatemi & McDermott, 2016). Mostly, they are measured through survey questions, in which an attitude object is presented as a stimulus, and the respondent must position him or herself on a bipolar scale. Typically, Multi-Item Likert scales are employed, so that an individual’s attitude towards the object is represented by the sum of the responses to each statement, or by some weighted combination of these scores.

Particularly, attitudes towards inequality represent a multifaceted concept, including perceptions, beliefs, and judgments about the distribution of resources within a society (Janmaat, 2013). Perceptions refer to subjective estimations about the scope of inequality (Castillo et al., 2022; Heiserman & Simpson, 2021). Instead, beliefs correspond to normative ideas about how inequality ought to be. Indeed, this dimension is frequently measured with indicators similar to the ones of perceptions, but situating individuals in an ideal scenario (Osberg & Smeeding, 2006). Finally, judgments represent evaluations of existing inequality and refer to how good, desirable, fair, or just individuals rate the current distribution (Kelley & Evans, 1993).

Inequalities stem from various social, economic, and political arrangements (McCall & Percheski, 2010), making several interconnected fields crucial for understanding attitudes toward inequality (McCarty & Pontusson, 2011). The way welfare states collect and redistribute resources through social programs and transfers significantly shapes societal inequality (Esping-Andersen & Myles, 2011; Korpi & Palme, 1998; Volscho & Kelly, 2012). Additionally, evaluations of taxes, redistribution, and wages are closely tied to perceptions, beliefs, and judgments about inequality (Bartels, 2005; Berens & Gelepithis, 2019; Bussolo et al., 2021; Choi, 2021; Fatke, 2018; García‐Sánchez et al., 2020; Iacono & Ranaldi, 2021; Trump, 2023). Understanding inequality thus requires delving into subjective perceptions of these interconnected issues. Indeed, the literature highlights various connections between perceptions, beliefs, and judgments about inequality, taxes, redistribution, and wages. For instance, individual perceptions of inequality influence normative ideas about how society should be structured (Pedersen & Mutz, 2019), support for public redistribution (Gimpelson & Treisman, 2018; Kuhn, 2011; Kuziemko et al., 2015; Trump, 2023), and attitudes toward progressive taxation (García‐Sánchez et al., 2020).

Beyond cross-sectional studies, researchers have also examined how attitudes toward inequality evolve, yielding mixed results. Cruces and colleagues (2013), using an experimental survey in Argentina, demonstrated the significant role of perceptions in shaping distributional beliefs. Their findings revealed that individuals who overestimated their relative social position became more supportive of redistribution when informed of their actual placement in the social hierarchy. Similarly, Campos-Vazquez et al. (2022) conducted an experimental study in Mexico, providing participants with objective information about income inequality and social mobility. Unlike the Argentine study, their results showed that altering perceptions of inequality did not lead to changes in participants’ normative beliefs about income distribution, social mobility, or tax rates.

### 2.2 Inequality Belief Systems

In response to the unsystematic nature of previous research, a new strand of the literature has emerged, examining the structure of attitudes toward inequality (Franetovic & Bertero, 2023). This approach focuses on how perceptions, beliefs, and judgments about economic disparities, redistribution, taxation, and wage allocation interact to form an interconnected inequality belief system (Bertero et al., 2024). This approach, rooted in the work of Converse (2006), complements the traditional latent variable model commonly used in attitude research. Latent models conceptualize attitudes as unobservable constructs that are reflected in observable evaluations of attitude objects (Eagly & Chaiken, 1993; Rosenberg, 1960). They rely on assumptions of local independence—where observed indicators are thought not to influence each other once the latent attitude is accounted for—and exchangeability—where adding more items only enhances reliability without contributing new information (Bagozzi, 1981; K. A. Bollen, 1989; K. Bollen & Lennox, 1991).

The belief system literature incorporates cognitive consistency and accuracy as core mechanisms, suggesting that attitudes develop incrementally through associations with related beliefs (Dalege et al., 2016). For instance, individuals might first perceive high levels of income inequality and judge them as fair or unfair (Time 1). Over time, they could associate this judgment with beliefs about the causes of inequality, such as the gender pay gap (Time 2), and later expand these associations to include political inaction (Time 3) or the role of race and religion in personal success (Times 4 and 5). In this process, individuals aim to minimize cognitive inconsistency by forming coherent stances on subjective inequality (Dalege, Borsboom, Harreveld, Waldorp, et al., 2017). However, belief systems must also balance consistency with accuracy, allowing for misaligned evaluations. For example, individuals might believe inequality is high due to the gender pay gap but see race and religion as irrelevant to the inequality equation.

This dual process generates two patterns. First, the expansion of belief systems involves nodes unequally, as some components—like those with strong initial associations—are more likely to connect with newer perceptions, beliefs, and judgments, resembling patterns of preferential attachment (Barabási & Albert, 1999; Dalege et al., 2016, 2018). Consequently, beliefs differ in centrality within the network. Second, aligned and misaligned evaluations are organized to coexist without psychological distress. To achieve this, belief systems exhibit high clustering, grouping coherent evaluations within the same substructures while placing mismatched ones in distinct areas of the network (Dalege et al., 2019).

Researchers in this field have primarily used two methodologies. On the one hand, scholars have used Correlational Class Analysis (CCA; Boutyline, 2017) or Relational Class Analysis (RCA; Goldberg, 2011). These techniques group individuals based on similar correlational patterns among their attitudes, mapping belief systems as networks of associations without assuming shared normative positions. For example, Kesberg et al. (2024) applied CCA to examine the validity of system justification theory (Jost & Van der Toorn, 2012), finding that social status negatively correlates with support for the status quo only within specific population segments, not universally. Using RCA, DiMaggio and Goldberg (2018) identified three distinct ways the U.S. public organizes attitudes toward the market: an “economistic” class favoring markets as beneficial, a “hostile worlds” class supporting markets but restricting morally contentious transactions (e.g., organ sales), and a “progressive” class endorsing markets with regulatory interventions to address market failures and protect public welfare.

A second class of network methods, introduced by Boutyline and Vaisey (2017) and refined through advancements in network psychometrics (Borsboom et al., 2021) and political psychology (Brandt, 2022; Brandt et al., 2019), represents attitudes as nodes within weighted and signed networks, with edges indicating partial correlations between survey items. Franetovic and Bertero (2023) applied this approach to study inequality attitudes in Chile, revealing an integrated belief system with a small-world structure. They also found that lower social groups exhibit higher connectivity, a feature linked to attitude strength (Dalege et al., 2019). Combining CCA with partial correlation networks, Bertero et al. (2024) identified two distinct types of belief systems in the U.S. and the Netherlands, showing that the organization of these systems significantly predicts support for public redistribution.

### 2.3 Research hypotheses

This section outlines our research hypotheses. Attitudes are conceptualized as networks of evaluations, where some nodes form more connections, bridging areas of the network and enhancing connectivity. These networks are typically clustered to balance accuracy and consistency, resembling small-world structures (Watts & Strogatz, 1998). Small-world properties have been validated across various contexts, including attitudes toward political candidates (Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017; Dalege et al., 2016) post-national citizenship identities (Schlicht-Schmälzle et al., 2018), job satisfaction (Carter et al., 2020), bio-based plastic (Zwicker et al., 2020), political values (Turner-Zwinkels et al., 2020), and inequality (Franetovic & Bertero, 2023). Based on this, we hypothesize:

*H1: The inequality belief system will exhibit a small-world structure.*

Beliefs differ in importance. For networks estimated with cross-sectional data, centrality reflects how strongly a node interacts with others, without indicating directionality—it may predict, be predicted by, or both (Bringmann et al., 2019). In social justice research, the perception of large income inequality is often treated as an independent variable, influencing attitudes like support for redistribution (Gimpelson & Treisman, 2018; Trump, 2023), ideal distributions (Pedersen & Mutz, 2019), and progressive taxation (García‐Sánchez et al., 2020). Conversely, the belief in public redistribution is typically a dependent variable shaped by factors such as social class (Langsæther & Evans, 2020), subjective social status (Choi, 2021), beliefs about intergenerational mobility (Alesina et al., 2018), social comparison processes (García‐Castro et al., 2022), trust in the political system (Franetovic & Castillo, 2022). These two attitudes are positively correlated (Gimpelson & Treisman, 2018; Kuhn, 2011; Kuziemko et al., 2015; Trump, 2023) and play a pivotal role in distributive justice research. Notably, Franetovic & Bertero (2023) found them to be the most central nodes in Chile's inequality belief system. Therefore:

*H2: Perception of large income inequality and belief in public redistribution will be the most central nodes in the inequality belief system.*

The first two hypotheses examine the attitudinal structure at the population level. However, full-sample data may mask structural heterogeneities (DiMaggio et al., 2018). Research shows that attitudes toward inequality vary by sociodemographic characteristics (Bobzien & Kalleitner, 2021; Lindh & McCall, 2020), and individuals’ social positions influence relational structures, with lower education, income, and social class linked to more densely connected networks of attitudes (Franetovic & Bertero, 2023).

To build on these findings, we investigate whether cognitive and emotional factors, particularly anger, moderate network structures. Anger plays a critical role in shaping attitudes toward inequality. U.S. citizens with lower social status report higher levels of anger, often driven by frustration, inferiority, and perceived injustice (Park et al., 2013). Anger not only reflects personal grievances but also has significant societal implications. Comparative studies reveal that angry individuals are less likely to support conservative economic parties and more likely to back progressive ones (Gonthier, 2023). Anger strengthens the link between perceptions of inequality and the willingness to engage in political action to address it (Leach et al., 2006), and mediates the relationship between perceived inequalities and psychological well-being (Vezzoli et al., 2023). These findings suggest that anger intensifies the relationships between distributive evaluations, moderating the structure of inequality belief systems by amplifying connections between attitudes towards inequality. Thus:

*H3: The structure of the inequality belief system is moderated by individuals’ anger towards inequality.*

Network approaches to belief systems provide a formalized theory of attitude change. Nodes vary in centrality, and changes in central nodes are expected to produce larger shifts in the network compared to peripheral ones (Brandt et al., 2019; Converse, 2006). This has been confirmed through simulations, where changes in central nodes create downstream effects, causing neighboring nodes to adjust their states (Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017). Similar effects, albeit weaker, have been observed in longitudinal studies of job satisfaction (Carter et al., 2020), COVID-19-related attitudes (Chambon et al., 2022), and political beliefs (Turner-Zwinkels & Brandt, 2022). Given the absence of panel data on subjective inequality—and cumulating with H2—this study simulates manipulations targeting each node to test whether:

*H4: Simulated manipulation attempts targeting the perception of large income inequality and the belief in public redistribution will produce downstream effects in the inequality belief system.*

## 3. Methods

### 3.1 Data and variables

We use the ISSP 2019—Social Inequality V module (ISSP Research Group, 2022), which includes several indicators of subjective inequality. We analyze U.S. data, collected with a multistage probabilistic design and Computer Assisted Web Interface methodology. The sample is representative of the population aged 18 years or older. The original dataset includes 1,852 individuals. Table 1 shows the 22 selected variables and their corresponding ISSP questions. High scores indicate high perceptions of inequalities, egalitarian beliefs, and judgments of unfairness about existing levels of social disparities. All variables are measured on a 1 to 5 scale, with the exceptions of *Judgment of unfair distribution[[1]](#footnote-1)* (1-4) and *Anger towards inequality* (0-10). Listwise deletion reduces the sample to 1,188 individuals[[2]](#footnote-2).

To cumulate with past research, the article includes twelve perceptions, seven beliefs, and three judgments about inequality in the U.S. (see Franetovic & Bertero, 2023). Respondents were asked to report their *Perception of large income inequality* and their *Perception of tax regressivity*. The analyses include ten explanations of inequality, also known as inequality beliefs (Mijs, 2018), which are items asking respondents to indicate how important they perceive a set of structural and individual factors to be for getting ahead in life (*Importance of wealthy family, parental education, own education, hard work, knowing the right people, political connections, giving bribes, personal race, religion,* and *sex*). Belief items ask respondents to express normative judgments on how they would desire society to be organized. The questionnaire included the *Belief in progressive taxation*, *public redistribution,* and *market redistribution*. Moreover, one survey battery taps into beliefs on just pay criteria, asking respondents to indicate whether they would agree on wages to be regulated based on the responsibility associated with the job, or on workers’ training levels, needs, and merits (*Pay criteria responsibility training, need, merit*). Finally, respondents judged the fairness of the existing income distribution in the U.S. (*Judgment of unfair distribution*), the extent to which politicians are distrusted (*Judgment of political distrust in redistribution*), and unsuccessful (*Judgment of failure of public redistribution*) in addressing and fighting inequality. Finally, the 2019 ISSP Social Inequality module measures, for the first time, individuals’ anger towards inequality. This item is addressed with the following survey question: “Some people feel angry about differences in wealth between the rich and the poor, while others do not. How do you feel when you think about differences in wealth between the rich and the poor in the U.S.?”.

[TABLE 1 ABOUT HERE]

### 3.2 Network estimation

Network estimation follows several steps (Borsboom et al., 2021). Variables are first selected through a literature review to ensure construct validity. Survey data is then analyzed using Graphical Models, which encode conditional dependencies as network edges and independencies as their absence (Lauritzen, 1996). The resulting undirected network represents the aggregate structure of the U.S. inequality belief system. Structural properties are analyzed, and parameter stability is tested using bootstrapping (Efron, 1979).

To address H1 and H2, a Mixed Graphical Model (mgm) is estimated (Haslbeck & Waldorp, 2020). This model accommodates variables measured at different scales and estimates parameters through a loop of node-wise regularized linear regressions. At the beginning of the analysis, variables are mean-centered and rescaled. Then, each variable is iteratively regressed on every other, while controlling for the remaining nodes. To avoid multicollinearity issues and to model specificity, mgm uses L1-penalized regression (LASSO) (Tibshirani, 1996). LASSO regularization induces sparsity in the network matrix, as it forces smaller coefficients to become exactly zero, effectively performing variable selection. The LASSO tuning parameter is searched with a model selection approach and is found by minimizing the Extended Bayesian Information Criterion, an extension of the BIC (Schwarz, 1978) that penalizes with additional intensity nonzero parameters . This strategy is extensively validated (Epskamp & Fried, 2018; Foygel & Drton, 2010; Haslbeck & Waldorp, 2020) and allows the quantification of node predictability. Since all variables are modeled as continuous, R2 values are reported, and edges are interpretable as regularized linear regression coefficients (Burger et al., 2022).

H1 and H2 are tested on the mgm network[[3]](#footnote-3). The small-worldness of the network, assessed using Telesford et al.’s (2011) test, compares clustering and connectivity with a lattice network of the same size. Clustering measures the extent to which nodes form cliques (Watts & Strogatz, 1998), and connectivity is evaluated via the Average Shortest Path Length[[4]](#footnote-4) (ASPL). Networks are small-world if their connectivity matches or exceeds a random network and their clustering is higher, producing values between −0.5 and 0.5. The centrality of network nodes is calculated with the Strength metric, which sums the absolute values of the edge weights of the relationships in which a node is involved (Opsahl et al., 2010). Strength captures direct, pairwise associations between attitudes, providing a robust measure of each node’s importance within the inequality belief system[[5]](#footnote-5).

H3 investigates whether the network structure estimated on the full sample hides structural heterogeneities that are produced by different levels of anger towards inequality. A common approach for testing research questions involving group differences is to split the sample by the levels of a third variable, estimate two network models, and compare them with a permutation-based Network Comparison Test (Borkulo et al., 2022). The split-sample strategy is commonly used by scholars employing a network approach to examine the structure of socio-political attitudes. Yet, these procedures are impeded by two shortcomings. First, data-split approaches reduce sample size, and thus statistical leverage; second, these strategies can only model a step moderation process, where the slope of a relationship can differ between two groups, but not within them. The Moderated Network Model (MNM) mitigates both problems (Haslbeck et al., 2021). Its edges are estimated with the same strategy outlined above, relying on a set of regularized linear regressions whose tuning parameter is obtained by minimizing the EBIC. However, in each of these regressions, the MNM adds a moderation effect of a selected variable. Therefore, MNM produces two parameter matrices, one for the pairwise and one for the three-way interactions. To address H3, this article fits an MNM in which anger towards inequality is specified as a moderator. H3 is confirmed if anger meaningfully moderates network edges.

H4 is tested with a network simulation that requires variables’ dichotomization[[6]](#footnote-6). Edges of this model represent associations between binary nodes and are estimated with logistic—rather than linear—regularized regressions. Hence, the mgm reduces to an Ising model (Ising, 1925), whose edges are interpretable as logistic regression coefficients (Borkulo et al., 2015). The Ising model can estimate two additional classes of parameters that are discussed in Section 3.3.

We evaluate the robustness of edge weights (Figures 2 and 4, Supplement) and of the moderation effects of anger (Table 2, Supplemental Material) with non-parametric bootstrapping (Epskamp et al., 2018), generating 10,000 resamples on which we re-estimate networks, to estimate 95% confidence intervals. Strength centrality stability is tested with case-dropping bootstraps, yielding the Correlation Stability (CS) coefficient, which should exceed 0.25, preferably 0.50. Bootstrapped difference tests compare edges or Strength scores, with non-overlapping intervals indicating significant differences.

Last, we adopt community detection techniques to investigate how nodes of the inequality belief system cluster together. To cumulate with the partial-correlation-based Exploratory Graph Analysis (EGA) technique, we adopt the Walktrap community detection algorithm (Golino et al., 2017). EGA has been shown to perform on par with or better than traditional dimensionality assessment methods like factor and parallel analysis[[7]](#footnote-7) (Golino et al., 2020). In the remainder of the Methods section, we detail our simulation of attitude change.

### 3.3 Network simulation

H4 is tested through a simulation of network dynamics using Ising’s model (Dalege, Borsboom, Harreveld, & Maas, 2017; Ising, 1925), where nodes represent endorsement or rejection of survey items (-1 or +1). The temperature parameter, governing system entropy, remains constant across simulations due to its correlation with attitude strength (Dalege et al., 2018). Two additional parameters, described by the Hamiltonian function, estimate the energy expenditure of the network configuration:

Each network node (Xᵢ to Xⱼ) has a threshold (𝛕ᵢ to 𝛕ⱼ) ranging from -1 to +1, indicating its likelihood of being endorsed (+1) or not (-1). The ω parameter models the strength of nodes interactions, with positive values for positive associations and vice versa. Configurations of the belief system where nodes with positive thresholds are connected with positive edges minimize energy expenditure, aligning with the Ising model’s principle that attitudes favor low-energy configurations.

The simulation models persuasion attempts targeting one node at a time and has already been applied to socio-political attitudes (Dalege, Borsboom, Harreveld, & Maas, 2017; Schlicht-Schmälzle et al., 2018). Manipulations increase node thresholds (𝛕), with the dependent variable being the sum score of attitudes towards inequality[[8]](#footnote-8) before and after each manipulation. H4 is supported if changes in the *perception of large income inequality* and *belief in public redistribution* cause downstream effects, where a node’s state change influences others. The simulation creates 23 samples of 3,000 individuals answering 22 survey items. In the baseline, all nodes have a threshold of -0.1; in all other samples, one node is set to +1[[9]](#footnote-9). Networks are estimated after each iteration, and sum scores are compared to assess structural changes.

## 4. Results

### 4.1 Modelling the network of attitudes towards inequality

Table 1 in the Supplemental Material shows descriptives of the 22 attitudes. U.S. citizens widely perceive economic disparities, support egalitarian distribution, and view current inequalities as unfair. They see income inequality as significant, the tax system as regressive, and success as mostly tied to hard work and education. Respondents favor progressive taxation, expect action from corporations and public institutions to reduce income differences, and prioritize merit in wage allocation. They also view political actors as disinterested and ineffective in addressing inequalities.

**[FIGURE 1 ABOUT HERE]**

Figure 1 illustrates the U.S. inequality belief system, with nodes representing the 22 perceptions, beliefs, and judgments, colored according to community detection results. The network is visualized using a force-directed layout (Fruchterman & Reingold, 1991), with edges indicating positive (blue) or negative (red) associations between items. The attitudes form a single, cohesive belief system, showing that U.S. citizens organize their views on inequality, taxation, redistribution, and wages into one mental framework.

The strongest positive associations in the model link explanations based on race and sex, political connections and knowing the right people, and perceptions of income inequality with support for public redistribution. The strongest negative associations in the network are those between explanations considering the importance of hard work and giving bribes, inequality beliefs pointing at the importance of wealthy families and hard work, and between the belief in public redistribution and responsibility as pay criteria.

Network edges reveal two main patterns. First, most associations are positive, reflecting the coherent organization of U.S. citizens’ high perceptions, egalitarian beliefs, and severe judgments about inequality. Second, the strongest connections occur between variables within the same conceptual domain. For example, pay criteria such as merit, responsibility, and training are strongly linked, as are the ten explanations of inequality, clustered at the bottom of Figure 1.

Structuralist explanations like religion, race, and sex are more likely to interact with each other than with individualist factors like hard work or education. Moreover, we also retrieve strong associations between different types of attitudes toward inequality, such as those between the perception of large income inequality and the belief in public redistribution, or between the perception of tax regressivity and the belief in progressive taxation. Moreover, believing in need as a pay criterion is largely unrelated to endorsing merit or responsibility. Therefore, not all semantically related attitudes strongly correlate.

These associations create four distinct network communities, each representing different domains of attitudes towards inequality. The structuralist community (yellow) focuses on societal divisions that contribute to inequality, such as race, religion, and sex. The individualist community (green) centers on factors tied to individual agency, including hard work, education, and responsibility, merit, and training as pay criteria. The mixed community (blue) encompasses meso-level explanations rooted in social contexts, such as the importance of knowing the right people, having political connections, or coming from a wealthy family. Lastly, the red community includes all judgments, perceptions, and beliefs related to both public and private redistribution.

Node predictability measures how much of a variable’s variance is explained by the network model. Pay criteria show the lowest predictability, suggesting they are less integrated into the network and influenced by factors external to the model. In contrast, the perception of large income inequality and the belief in public redistribution have the highest predictability, indicating that their levels are primarily determined by other variables included in the network model. This supports the validity of item selection, as key variables in inequality research are well-modeled by the inequality belief system.

According to belief system theory, this system is expected to exhibit a small-world structure (H1), balancing individuals’ needs for accuracy and consistency. Structurally, the network shows low density, with only 30.6% of possible edges present. Compared to a random network, it has a higher average shortest path length (ASPL) and lower clustering coefficient, resulting in a small-world score of 0.228, confirming H1.

We also hypothesize that the belief in public redistribution and the perception of large income inequality are the most central nodes (H2). Figure 2 shows their high Strength centrality scores, indicating strong and frequent connections with other nodes. These variables consistently rank as the most central in both the full-scale and bootstrapped networks, with the belief in public redistribution slightly more central overall. Notably, centrality stability is high, with results remaining reliable even when 75% of the sample is dropped. Peripheral nodes include the four pay criteria and the belief in market redistribution, showing that high endorsement does not guarantee centrality. For example, while the support for market redistribution has a higher average endorsement than public redistribution, the latter is far more central, underscoring its pivotal role in the inequality belief system.

[FIGURE 2 ABOUT HERE]

### 4.2 Estimating structural differences in the network of attitudes towards inequality

Figure 3 confirms our hypothesis (H3) that anger toward inequality moderates the belief system’s structure. Each panel shows networks estimated at different anger levels, with anger depicted as a separate white node. More than 25 edges are strongly influenced by anger, as detailed in Table 2 of the Supplemental Material, with effects consistently found in over 83% of bootstrapped samples, ensuring robust results.

[FIGURE 3 ABOUT HERE]

The strongest moderation effect involves the relationship between the judgment on the failure of public redistribution and the belief in public redistribution. The magnitude of this moderation effect equals 0.064. Indeed, when anger scores zero, a unit increase in the belief in public redistribution corresponds to a 0.025-unit increase in the judgment of its failure. As anger rises, this relationship strengthens. For example, when anger scores 3 (top-right panel of Figure 3), the relationship increases to 0.217, reaching 0.473 and 0.665 in the bottom panels. This moderation shows that anger toward inequality amplifies the link between these variables. Therefore, Figure 3 underscores that the associations between distributive attitudes are generally stronger for individuals who are angry towards inequality.

Anger strongly moderates relationships between explanations of inequality. As anger increases, distinctions between individualist, structuralist, and mixed explanations become more pronounced. For example, at low anger, perceiving a wealthy family as important weakly predicts considering sex as significant, but this link strengthens significantly at high anger. Similarly, the connection between perceiving the importance of coming from a wealthy family and political connections grows for angry individuals. In contrast, anger sharpens divides between structuralist and individualist factors. For example, when anger is low, parental education and race are unconnected, but at high anger, they are strongly and negatively connected. Similarly, the weak negative association between personal education and giving bribes becomes strongly opposed.

Anger also alters the role of specific variables, such as the importance of education and the belief in market redistribution. At low anger, education is weakly associated with the belief in market redistribution, but this link becomes much stronger at high anger. As a result, the belief in market redistribution, typically peripheral in the network, becomes more central when anger is high, interacting more strongly with other perceptions and beliefs.

At low levels of anger (top panels of Figure 3), the inequality belief system mirrors the full sample network (Figure 1), with four distinct network communities. However, as anger increases, the network consolidates into fewer communities, reflecting stronger interactions among distributive attitudes. When individuals experience higher anger (bottom panels of Figure 3), their belief system is structured into three communities, with explanations of inequality merging into a single group. This suggests that heightened anger drives U.S. citizens to see individual, structural, and mixed factors as increasingly interconnected in shaping social inequalities.

Anger intensifies most of the associations within the network, making attitudes toward inequality more contentious. Indeed, at low anger, the networks show weaker connections and fewer negative associations; for example, mean absolute edge weights are 0.061 and 0.068, with 46 and 59 negative edges when anger scores 0 and 3. At higher anger (scores 7 and 10), mean edge weights increase to 0.101 and 0.127, and negative edges rise to 62 and 63. This intensification means positive associations become stronger, while null or weakly negative relationships turn strongly negative, leading to a more polarized and tightly connected belief system.

### 4.3 Simulating attitude change

To test whether changes in central nodes trigger larger adjustments than peripheral ones, variables were dichotomized, and an Ising simulation was conducted. Table 1 in the Supplemental Material provides descriptives, and Figure 4 shows the resulting network (top) and node strength centrality (bottom)

[FIGURE 4 ABOUT HERE]

In Figure 4, edges represent regularized logistic regression coefficients, with the layout replicating Figure 1 for comparability. The Ising network has similar density (0.32) and retains the strongest associations from the full-scale model, such as links between race and sex, tax regressivity and progressive taxation, and large income inequality and public redistribution. Strength scores and communities remain consistent, with the perception of large income inequality, the importance of race, and the belief in public redistribution as the most central nodes, while pay criteria and the belief in market redistribution are the most peripheral.

Figure 1 in the Supplemental Material compares standardized centrality scores from the two models, showing minimal variation in rankings. The main exception is the belief in public redistribution, which ranks first in the mgm network but third in the Ising model. In both models, the perception of large income inequality, the importance of race, the belief in public redistribution, and the importance of wealthy families consistently score highest in centrality, with overlapping bootstrapped confidence intervals for most differences. However, the perception of large income inequality and the belief in public redistribution remain more central than all other nodes. Furthermore, the CS coefficient remains high (0.75), and the Ising network is confirmed to have a small-world structure (0.223).

[FIGURE 5 ABOUT HERE]

H4 predicts that changes in central nodes will produce downstream effects, triggering broader adjustments in the inequality belief system. To test this, we simulate manipulations targeting one node at a time by increasing its threshold—a parameter modeling the predisposition to endorse each attitude—from -0.1 to +1, while keeping the thresholds of other nodes fixed at -0.1. According to the Hamiltonian function, increasing a node's threshold does not guarantee a state change (i.e., from “not endorsed” to “endorsed”), as nodes are influenced not only by their predisposition but also by their connections to other nodes (ω parameter).

Figure 5 presents the results of the simulated manipulations through a forest plot showing the network sum scores after each intervention. When all thresholds are set to a moderately negative value (-0.1), the network sum score is -5.462 (CI = -5.721, -5.203), indicating a moderately negative configuration of attitudes. This additive index ranges from -22 (rejection of all items) to 22 (endorsement of all items).

The dashed reference line in Figure 5 distinguishes between successful and unsuccessful manipulations. All dots have confidence intervals to the right of this line, indicating that each manipulation significantly altered the network sum score. A dotted reference line, placed 2 units further to the right, highlights downstream effects. Nodes with confidence intervals beyond this line not only changed their state but also triggered broader adjustments in the network, reflecting downstream effects on the inequality belief system.

Eight nodes produce changes exceeding two units, confirming and extending H4. These include the perception of large income inequality, the importance of race, coming from a wealthy family, and personal sex, the belief in public redistribution and progressive taxation, the perception of tax regressivity, and the judgment of failure of public redistribution. A comparison between Figure 5 and the centrality table in Figure 4 shows a strong correlation between Strength centrality and the magnitude of sum score changes, as the most central nodes tend to produce the largest downstream effects. Exceptions include the judgment of failure of public redistribution and the importance of sex, which have moderate centrality but still trigger substantial network changes when manipulated.

## 5. Discussion

Attitudes towards inequality are composed of perceptions, beliefs, and judgments (Janmaat, 2013). To validly study this multifaceted concept, we selected 22 ISSP questions surveyed in the United States. Variable selection cumulated with past research adopting a network approach to study public attitudes towards inequality, redistribution, taxation, and wages (see Franetovic & Bertero, 2023).

The structure of attitudes towards inequality at the population level was studied through a mgm, which rendered survey items as nodes of a weighted and signed network. The disparate set of evaluations is organized in a coherent belief system, as variables tapping different domains and different dimensions are organized into a single network component. Moreover, the network has small-world characteristics. At a theoretical level, this is motivated by the cognitive balance between the need for consistency and the need for accuracy (Dalege et al., 2016). The first phenomenon prompts individuals to hold coherent attitudes, to reduce psychological distress. On the opposite, the need for accuracy would drive respondent to adopt their position on each survey item independently from their other ideas on the related perceptions, beliefs, and judgments about inequality. The two tendencies are balanced by organizing coherent items into the same network cluster, and misaligned ones in different regions of the network.

Within this network, the strongest associations involve the explanations of inequality, the perception of large income inequality, and the belief in public redistribution. Results showed that perceiving personal sex as a key variable for personal success is highly predictive of considering religion and race as important, and vice versa. In the same fashion, explanations pointing at the individual agency, such as the role of hard work, and personal and parental education are strongly tied in the network. Although researchers have long distinguished between individualist and structuralist explanations of inequality (also referred to as “inequality beliefs” or “stratification beliefs”) (Kluegel & Smith, 1981), most of these perceptions correlate positively empirically (Mijs, 2018). Consistently, most of the associations between these two kinds of explanations were positive. The only exception to this pattern regards the belief in the importance of hard work, which contrasts with considering bribes, coming from a wealthy Importance of wealthy family, and personal sex as important. This finding is interpretable as a corroboration of American exceptionalism rather than a rejection of the co-occurrence of explanations of inequality. Indeed, a great deal of attitude research showed the relevance of meritocratic beliefs and individualist explanations of inequality in the U.S.(Alesina & Glaeser, 2004; McCall, 2013; Shariff et al., 2016). This was also captured in ISSP survey data, where this item is the most endorsed[[10]](#footnote-10). We integrate these findings by showing that, compared to what was observed in other highly unequal contexts (Franetovic & Bertero, 2023), the belief in hard work is at least partially at odds with other explanations of inequality in the U.S.

Two other nodes have important connections within the network of attitudes. These are the perception of large income inequality, and the belief in public redistribution. These variables are strongly and positively correlated and also interact with the other perceptions, beliefs, and judgments about inequality, redistribution, taxation, and wages. Consequently, these nodes have the highest centrality scores. This reaffirms the importance that the literature on distributive justice has long attributed to how people perceive income distribution and support public redistribution (Alesina et al., 2001; Alesina & Giuliano, 2009; Janmaat, 2013; Kuhn, 2011, 2019; Lübker, 2004; Shepelak & Alwin, 1986). Indeed, perceived income inequality was found to be a strong predictor of belief in public redistribution in several contexts (García‐Sánchez et al., 2020; Trump, 2023). Furthermore, perceived inequality is even more important than objective inequality in predicting redistributive preferences across contemporary societies (Bussolo et al., 2021; Trump, 2023).

The least central nodes in the network were the four pay criteria. The desired principles for the allocation of wages were found to be marginal also in a previous contribution adopting a network approach to study attitudes towards inequality (Franetovic & Bertero, 2023). The findings showed that these variables are rather compartmentalized. Endorsing a meritocratic criterion is highly associated with praising the principle for which wages should be determined by the amount of responsibility associated with the job, and by the educational level of the worker. However, these beliefs are detached from desiring wages to be determined based on workers’ needs. The criteria rarely interact with other network nodes. The few associations they hold in the network are with individualist explanations of inequality.

The estimation of a network model on full sample data relied on the assumption that attitudes towards inequality are structured in the same way across all population strata. Yet, this assumption is challenged by past research showing that the levels (Bobzien & Kalleitner, 2021; Lindh & McCall, 2020) and the structure (Franetovic & Bertero, 2023) of attitudes towards inequality vary across the population. In exploring these differences, researchers focused on the role of socioeconomic variables, studying how individuals of different social positions understand inequality. We undertook a complementary approach, by investigating the role that a cognitive variable might have in this process. The MNM showed that anger strongly moderates more than 20 edges, hence impacting the structure of this construct. The strongest moderation effects involved the belief in public redistribution and the judgment on its failure. This association becomes considerably stronger as the anger of U.S. respondents gets higher. This means that when individuals are particularly upset by existing levels of inequality and think that the government should reduce income differences between individuals, they tend to logically judge more strongly the political efforts made to date to reduce it as unsuccessful. Other important moderation effects regarded the relationships between explanations of inequality. When individuals are content with the level of U.S. inequality, they tend to endorse individualist and structuralist explanations altogether. This mirrors the schema that was found in the full sample, where most of these variables are positively related. However, increasing levels of anger are associated with greater misalignment of explanations of inequality. Anger towards inequality led respondents to perceive a discordance between explanations pointing at the role of parental and individual education, giving bribes, and peoples’ race, which became negatively associated in the MNM. Yet, the structuralist and individualist explanations of inequality backed by angry individuals are not fully detached, as they still perceive most of these explanations to cooccur in determining personal success.

These moderation effects produced two patterns. First, the attitudes of the angry U.S. public are more misaligned than those of the content. Indeed, when anger is high, the selected variables show a greater number of negative associations. Second, regardless of their signs, the associations between perceptions, beliefs, and judgments are stronger when individuals are angry about inequality. These results suggest that cognitive attachment to the problem of inequality might have two effects. It could drive individuals to hold potentially conflictual attitudes, and it could increase the interdependence between the evaluations composing this multidimensional construct.

Studying the structure of attitudes towards inequality is important because can generate inferences on attitude change. To test this possibility, we reduced the survey variables to dummy entities and performed an Ising estimation followed by a network simulation. The network estimated on dichotomous variables was remarkably similar to the mgm. The strongest associations of the full-scale model were correctly retrieved in the Ising network, which also preserved a small-world structure. Consequently, nodes that were central in the first network remained the most important vertices of the second. This allowed for testing the fourth research hypothesis, predicting a positive relationship between nodes’ centrality and attitude change after a manipulation attempt. The manipulations were simulated by increasing the nodes’ threshold one at a time. All manipulations were strong enough to produce the change of state of the targeted node. Their changes of states reverberated in the network, producing variations in its sum score. H4 was confirmed, as manipulations targeting the perception of large income inequality and the belief in public redistribution -the most central nodes- produced downstream effects. Additionally, the simulation showed a strong association between node centrality and the magnitude of attitude change. Indeed, also other highly central nodes produced huge changes in sum scores. Yet, attitude change is not necessarily a linear function of nodes’ embeddedness, as evaluations that are strongly and/or frequently related to other items can still produce variations of modest entities. This was the case of the perception of the importance of knowing the right people and of the judgments of unfair distribution. These variables had strong and numerous connections with other explanations of inequality, perceptions, and judgments. Yet, their state change was not sufficient to produce changes in the state of neighboring nodes. The results of the simulation are compatible with the findings of other research adopting a combination of network estimation and simulation to study attitudinal change in other research domains. Downstream effects were detected for attitudes towards political candidates (Dalege, Borsboom, Harreveld, & Maas, 2017) and post-national citizenship (Schlicht-Schmälzle et al., 2018), and their sizes are comparable to those found in this article.

## 6. Conclusions

The three aims of this paper produced three contributions to the literature on social justice research and network science. First, the article *modeled* attitudes towards inequality as a network of interacting evaluations regarding inequality, redistribution, taxation, and wages. This improves the current understanding of this construct, as it is usually studied through the lens of latent approaches. Adopting this modeling strategy shows that its components strongly interact, being part of a small-world belief system where the perception of income inequalities and the belief in public redistribution are central. Network analysis of multivariate data allows for the study of intra-dimensional associations (i.e.: the ones between perceptions, beliefs, or judgments), that are usually flattened to synthetic indexes in attitude research (i.e.: one mean score for each set of perceptions, beliefs, and judgments). Second, the article estimated structural differences in the network of attitudes towards inequality, demonstrating that cognitive factors produce changes in how people pack together their different evaluations. In doing so, the article innovated by adopting a moderated network model, which overcame most of the limitations of the split-sample approaches. Roughly a third of the associations composing the belief system were moderated by self-reported levels of anger towards inequality. This result reaffirms the importance of complementing the analyses of population-level attitudinal data with an investigation of the factors that produce variations in their levels and/or associational structure. Third, the theory and methodology at the core of the network approach to attitude provided the basis for simulating opinion change. The attitudes of the respondents were manipulated to show that changes in the levels of the perception of income inequality and the belief of public redistribution produce wider readjustments in the network if compared with simulated manipulation attempts targeted at peripheral nodes of the belief system.

The three research lines of the article were also limited in several ways. Regarding network modeling, panel data are needed to study attitudes towards inequality as an individual-level and dynamic construct (Brandt & Morgan, 2022). Longitudinal network methodologies are already available (Borsboom et al., 2021; Haslbeck & Waldorp, 2020). Thus, researchers are impeded by the shortage of highly granular and longitudinal data on subjective inequality. These data would provide a better fit between the theory of belief systems -positing they are implicit cognitive structures located in the mind of the individuals- and their empirical scrutiny -mostly anchored to cross-sectional data. Moreover, panel models would allow for relaxing a strong assumption of network approaches to attitudes: the fact that the belief systems have the same conceptual extension for all individuals. Indeed, belief systems encompassing subjective evaluations of inequality are likely to differ in size, possibly depending on the relevance inequality has for each individual. Concerning the estimation of structural differences in the network of attitudes, we adopted a deductive approach. Researchers have already shown that the levels (Bobzien & Kalleitner, 2021; Lindh & McCall, 2020) and the structure (Franetovic & Bertero, 2023) of attitudes towards inequality are influenced by objective measures of social stratification. Since their levels were also known to be influenced by anger towards inequality (Leach et al., 2006; Vezzoli et al., 2023), our work tested the impact this emotion has on the attitudinal structure. However, the investigation of structural differences with a theory-based approach is doomed to be unsystematic. Newly developed correlational methodologies might help explore these data heterogeneity inductively (Boutyline, 2017).

Finally, the simulation of network dynamics followed an idealized model, borrowed from ferromagnetism. Although the application of the Ising model to attitude change is fruitful for the formalization of the theory on belief system dynamics, straightforward inferences to real-world intervention scenarios might be improper. Indeed, this parsimonious simulation relied on a limited set of parameters and did not consider the feasibility of producing a change in the targeted attitudes. Central nodes might be the best vehicles of change in the network. Yet, being highly embedded in the network, they might also be the most resilient network components. Future research might proceed on this research line by combining well-developed experimental designs (e.g.: Mijs & Hoy, 2022) with a network approach to attitudes, exploiting the potential of network intervention analysis (Blanken et al., 2019).

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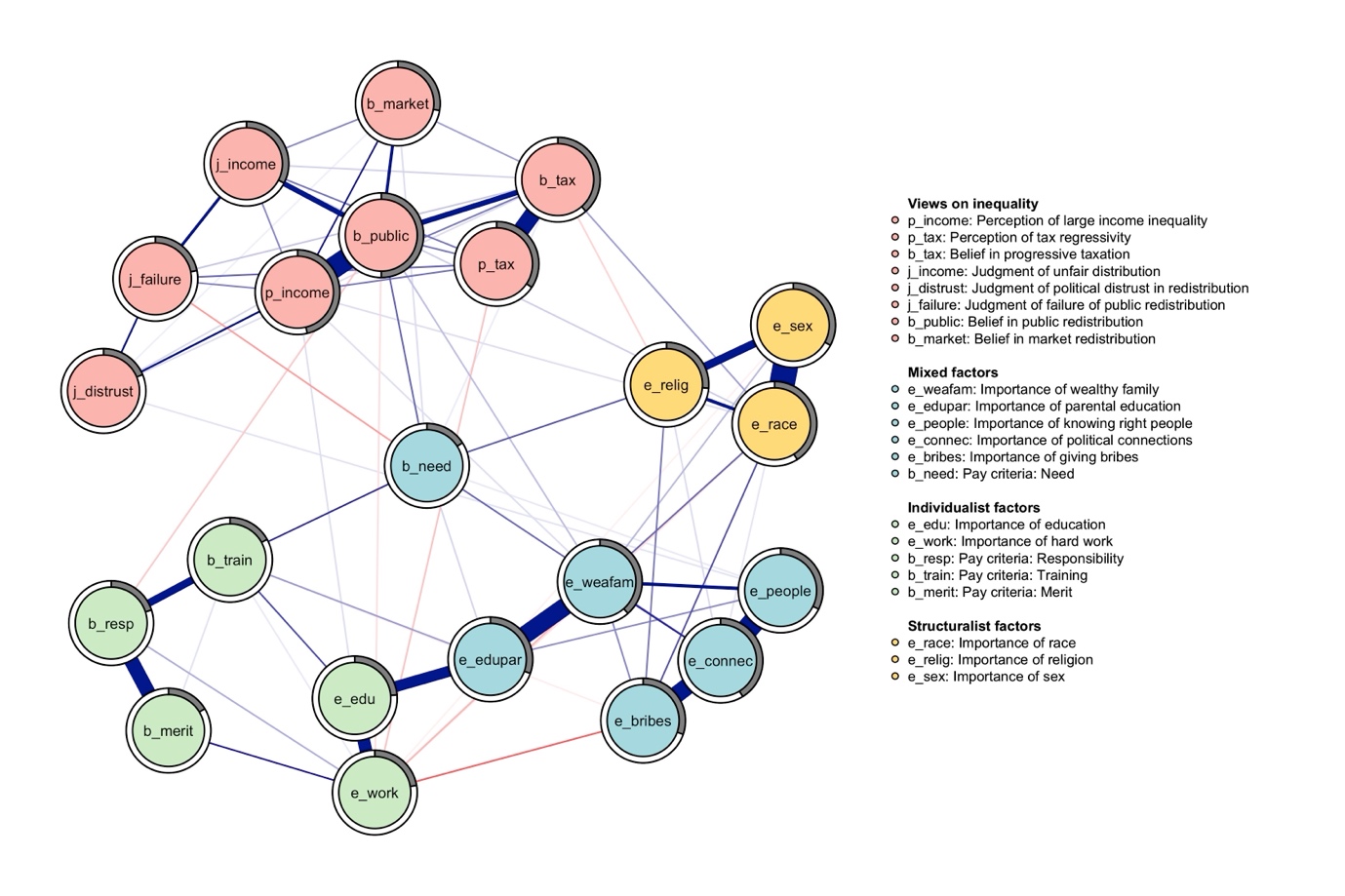
# V. Tables and Figures

Table 1: Labels and survey questions

|  |  |  |
| --- | --- | --- |
| **Label** | **Question** | **Type** |
| p\_income | To what extent do you agree or disagree with the following statement: Differences in income in the U.S. are too large. \* | Perception |
| p\_tax | Generally, how would you describe taxes in the U.S. today for those with high incomes? | Perception |
| e\_weafam | [How important is] coming from a wealthy Importance of wealthy family [for getting ahead in life?] \* | Perception |
| e\_edupar | […] having well-educated parents […] \* | Perception |
| e\_edu | […] having a good education yourself […] \* | Perception |
| e\_work | […] hard work […] \* | Perception |
| e\_people | […] knowing the right people […] \* | Perception |
| e\_connec | […] having political connections […] \* | Perception |
| e\_bribes | […] giving bribes […] \* | Perception |
| e\_race | […] a person’s race […] \* | Perception |
| e\_relig | […] a person’s religion […] \* | Perception |
| e\_sex | […] being born a man or a woman […] \* | Perception |
| b\_tax | Do you think people with high incomes should pay a larger share of their income in taxes than those with low incomes, the same share, or a smaller share? \* | Belief |
| b\_public | It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes. \* | Belief |
| b\_market | It is the responsibility of private companies to reduce the differences in pay between their employees with high pay and those with low pay. \* | Belief |
| b\_resp | [How important do you think that ought to be in deciding pay?] How much responsibility goes with the job \* | Belief |
| b\_train | […] The number of years spent in education and training. \* | Belief |
| b\_need | […] Whether the person has children to support. \* | Belief |
| b\_merit | […] How well he or she does the job. \* | Belief |
| j\_income | […] How fair or unfair do you think the income distribution is in the U.S.? | Judgment |
| j\_distrust | […] Most politicians in the U.S. do not care about reducing the differences in income between people with high incomes and people with low incomes. \* | Judgment |
| j\_failure | How successful do you think the government in the U.S. is nowadays in reducing the differences in income between people with high incomes and people with low incomes? | Judgment |

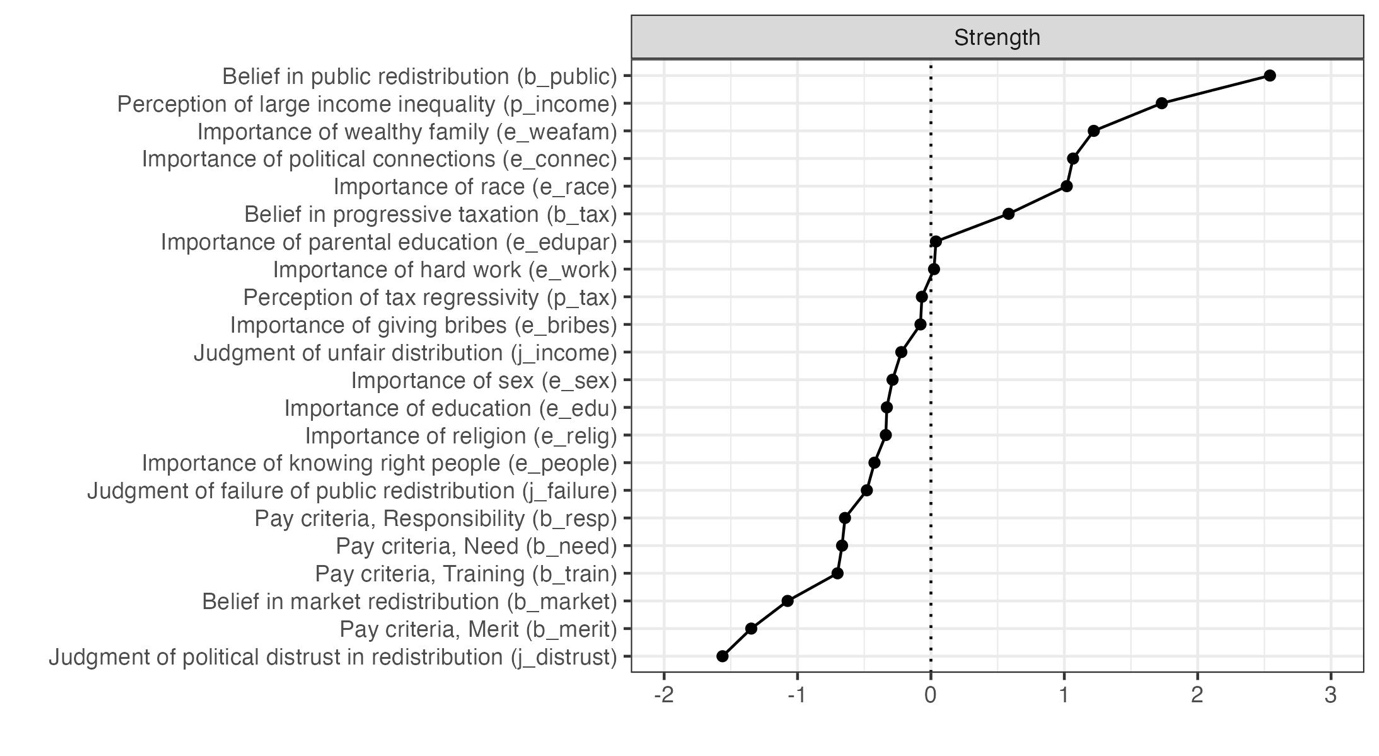
*Caption:* Squared brackets indicate common prompts between different items. The polarity of asterisked variables was inverted to have maximum values aligned with high perception, egalitarian beliefs, and critical judgments of existing inequality.

Figure 1: Mixed Graphical Model - Network of Attitudes Towards Inequality



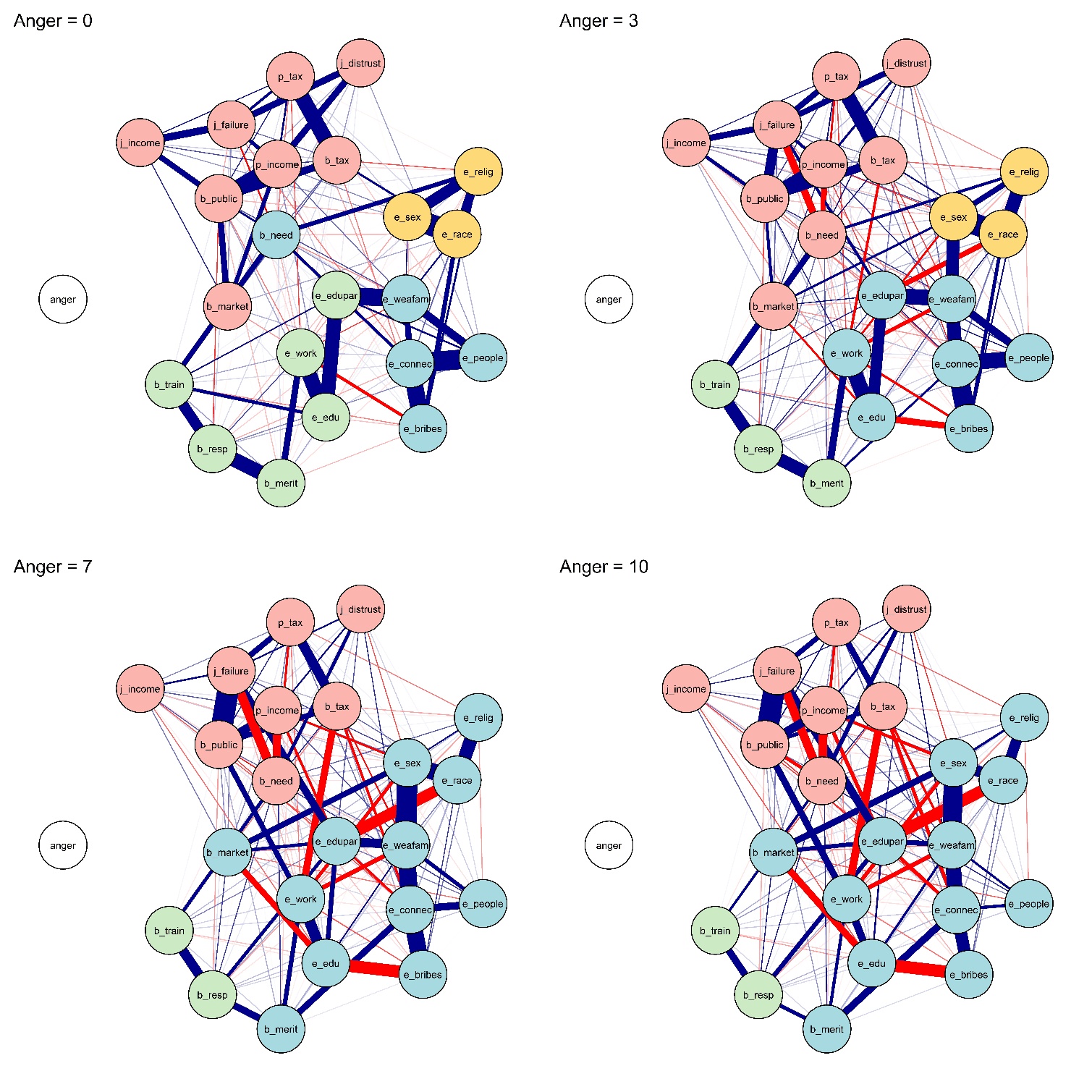
*Caption:* The network of attitudes towards inequality. Variables are represented as nodes, which are connected by weighted and signed edges. Nodes are colored according to their theoretical classification in perceptions, beliefs, and judgments about inequality. The circular shape around each node plots the partition of its variance that is explained by the model. Ties are indicative of the unique variance shared between each item pair. Their width is proportional to the strength of the corresponding associations. Blue edges represent positive linear influences, red negative ones.

Figure 2: Node centrality



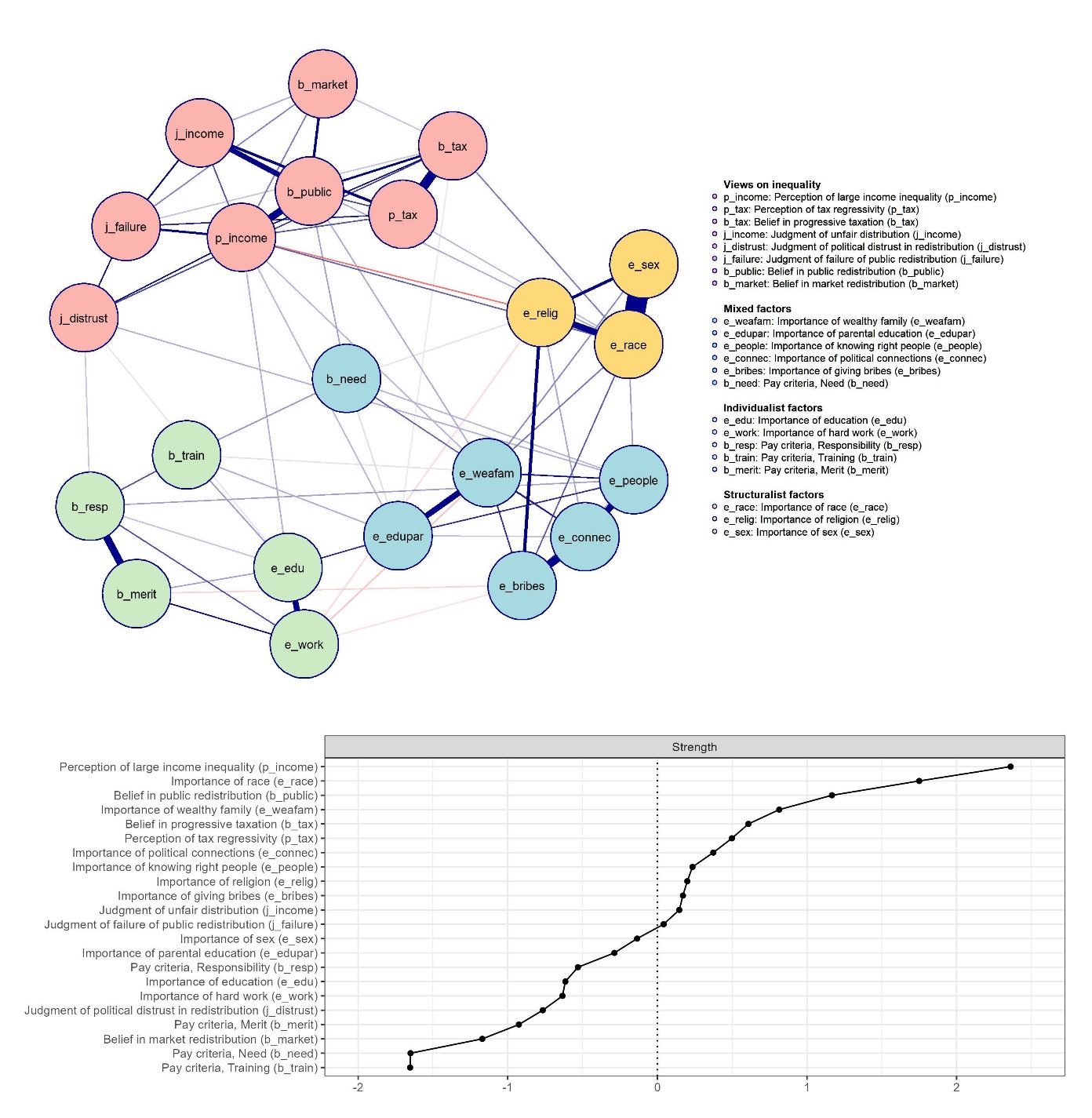
*Caption:* Strength centrality of GGM’s nodes. Each row shows one node and its centrality, measured in z-scores.

Figure 3: Moderated Network Model - Network of attitudes towards inequality



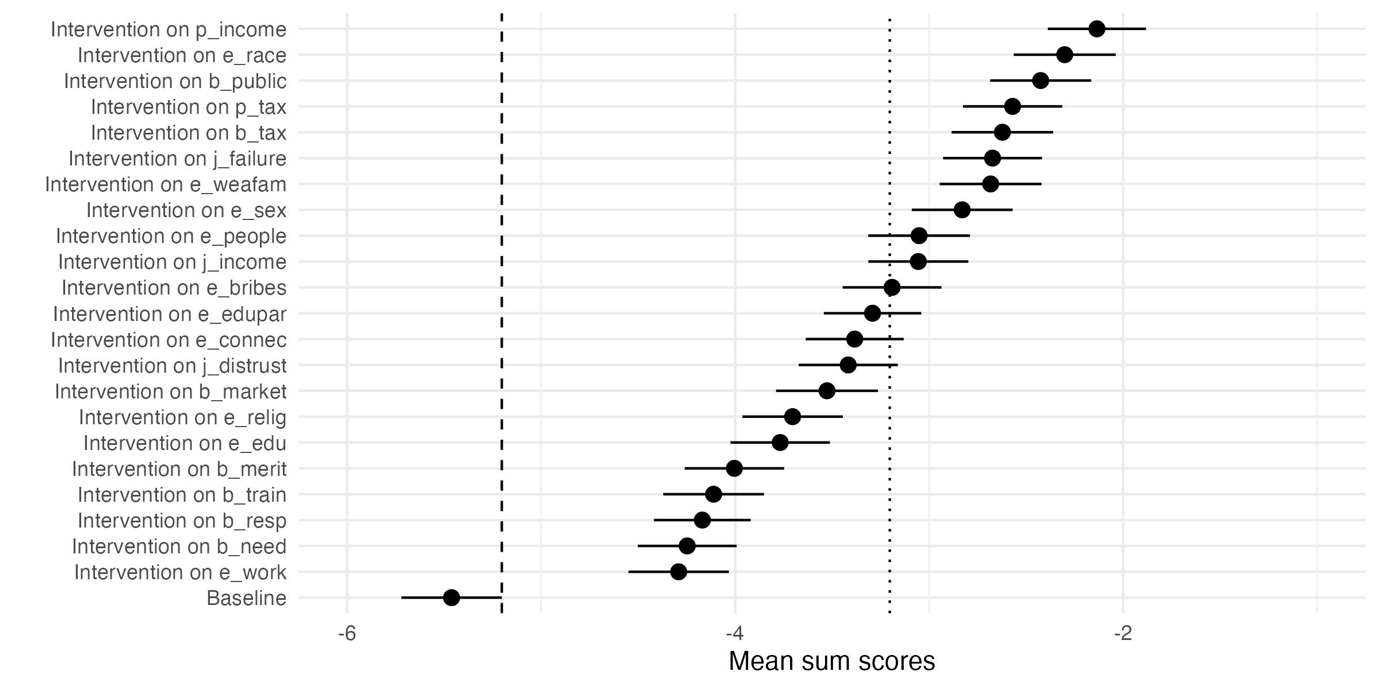
*Caption:* Each panel shows the result of a GGM estimation at a fixed level of the moderating variable, anger. Nodes are colored according to their classification in perceptions, beliefs, and judgments. Anger is plotted in white for clarity. Weighted and signed edges indicate conditional associations. Moderation effects are detectable by observing variations in edge color and/or width.

Figure 4: Ising Model - Network of attitudes towards inequality and centrality table



*Caption:* The top panel shows the results of the Ising estimation. The bottom panel shows z-scores of Strength centrality.

Figure 5: Results of simulated manipulation attempts



*Caption:* Each row is associated with a simulated manipulation attempt targeting one network node. Dots and confidence intervals show the mean sum score of the network after each intervention. The dashed line on the left separates successful versus unsuccessful manipulations. The dotted line on the right represents the threshold for downstream effects.

1. In the remainder of the article, network nodes are indicated in italics. [↑](#footnote-ref-1)
2. Additional analyses reveal missing cases do not impact meaningfully on the final sample. Figure 6 of the Supplemental Material shows that variables present between 2% and 11% of missing cases. Thus, nonresponses were fairly distributed between the selected variables. Moreover, Table 3 of the Supplemental Material shows that the means of the variables do not differ significantly between the original sample and the reduced one [↑](#footnote-ref-2)
3. As a robustness check, H1 and H2 are also tested on the binary network (see Results section). [↑](#footnote-ref-3)
4. To cumulate with past research, the clustering coefficient and the ASPL are calculated from the absolute and unweighted adjacency matrix. [↑](#footnote-ref-4)
5. We refrain from computing additional centrality metrics due to concerns regarding their underlying assumptions, which may not hold in a network of beliefs. Specifically, research by Bringmann and colleagues (2019) has shown that metrics like betweenness and closeness centrality assume influence flows via the most efficient paths within a network. However, this assumption is particularly problematic in belief systems, where nodes represent attitudes—constructs that lack the agency of social actors to direct or receive influence actively. Additionally, Dablander and Hinne (2019) combined partial correlation networks with Directed Acyclic Graphs to demonstrate that Strength, unlike Betweenness and Closeness, correlates strongly with causal influence. Guided by these insights, we rely on Strength to evaluate both H2 and H4, ensuring that our approach remains theoretically appropriate and methodologically sound for understanding belief networks. [↑](#footnote-ref-5)
6. Variables were truncated considering their mean values. Descriptives are made available in Table 2 of the Supplemental Material. Additional analyses confirmed dichotomization of all nodes following different criteria (truncation at two, or three out of five points) does not impact the estimated network meaningfully. [↑](#footnote-ref-6)
7. For a throughout discussion on the performance of EGA, its mathematical equivalence with factor analysis, and the adoption of the Walktrap algorithm for partial correlation networks, we refer interested readers to relevant validation studies (see Christensen et al., 2023, 2024; Christensen & Golino, 2021). [↑](#footnote-ref-7)
8. That is, the sum of the values of the state of all nodes (either -1 or +1). Hence, the sum scores range between -22 (all evaluative reactions are not endorsed) and +22 (every item is endorsed). [↑](#footnote-ref-8)
9. Parameters are selected to maintain comparability with the other studies adopting this simulation strategy (Dalege, Borsboom, Harreveld, & Maas, 2017; Schlicht-Schmälzle et al., 2018). [↑](#footnote-ref-9)
10. Respondents indicated it has an importance of 4.342 on a five-point scale (See Table 1 in the Supplemental Material). [↑](#footnote-ref-10)