# **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 represents one of the greatest challenges in contemporary societies, and it has been extensively studied in the U.S. The rise of disparities between social groups has reached unprecedented levels over the last decades (Atkinson et al., 2011; Keeley, 2015; Lansing & Markiewicz, 2018), establishing wide differences in the conditions under which people develop their lives (Wilkinson & Pickett, 2009). However, the widening of social gaps has not led to a corresponding increase in people’s concern about inequality (Kenworthy & McCall, 2007; Lierse et al., 2022; Lübker, 2004), highlighting that individuals tend to misunderstand the size of inequality, usually underestimating but sometimes overestimating it (Chambers et al., 2014). Therefore, the distribution of resources across societies does not have a direct link to how people understand inequality (Trump, 2023). The rise of disparities, coupled with the complex relationship between objective and subjective inequality, has made the study of people’s attitudes towards inequality a field of great scientific development in recent years across sociology (Mijs, 2019), political science (Larsen, 2016), economics (Luttig, 2013), and social psychology (Hegtvedt & Isom, 2014).

Research on distributive justice has traditionally relied on the latent variable approach, which consolidates multiple perceptions, beliefs, and judgments into mean indices. 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 investigated the *levels* of these attitudes (i.e., the extent of individual endorsement) while overlooking the cognitive *structure* in which they are embedded. However, attitudes do not exist in isolation; they are part of a broader belief system (Converse, 2006). Recent interdisciplinary research at the intersection of network science, sociology, political science, and psychology has provided innovative methodologies for analyzing the multifaceted components of attitudes towards inequality and understanding their structural organization. A new scholarship in distributive justice indicate that these attitudes form inequality belief systems, consisting of interconnected evaluations about the allocation of resources within a society, and related issues like redistribution, taxation, and wages (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 stances on inequality to understanding how these stances are organized within a broader belief system (Brandt & Sleegers, 2021; Dalege et al., 2016). However, the network approach to studying the structure of attitudes towards inequality faces two primary limitations. Methodologically, researchers frequently use Correlational Class Analysis ([CCA] Boutyline, 2017)  or partial correlation networks from network psychometrics (Borsboom et al., 2021; see Methods section). When examining variations in belief systems across social groups, these methods are often applied with a split-sample approach. For example, CCA partitions the sample into groups of individuals with shared socio-economic attitudes, presenting these associations as separate correlational networks (DiMaggio & Goldberg, 2018; Hunzaker & Valentino, 2019; Kesberg et al., 2024). Another common strategy is to stratify samples by socio-demographic variables and fit partial correlation networks for each subgroup (Franetovic & Bertero, 2023; Schlicht-Schmälzle et al., 2018). While these approaches offer valuable insights, they reduce statistical power and impose a step-moderation function, which assumes that belief system structures differ only between groups and not within them.

Additionally, the empirical contributions adopting a network approach to study attitudes towards inequality are characterized by a substantive limitation. Indeed, the field of study related to inequality belief systems has yet to test a critical proposition from Converse's work regarding opinion change. According to this view, when individuals revise a component of their belief system, related beliefs are expected to realign accordingly (Brandt & Sleegers, 2021; Converse, 2006). For instance, heightened perceptions of income inequality might lead citizens to advocate for stronger redistributive policies from politicians.

To address the methodological and substantive limitations, we craft a tripartite analytical strategy. First, we *model* attitudes towards inequality as an inequality belief system. The network approach allows us to retrieve the backbone of the connections occurring between the components of attitudes towards inequality that are usually hidden by the adoption of a latent variable framework. We do so by *estimating* a partial correlation network on ISSP data tapping attitudes towards inequality in the U.S. This results in a weighted and signed network that gives insights into the unique variance shared between beliefs, judgments, and perceptions of income inequality and related topics. Second, we *estimate* how the structure of the inequality belief systems varies within the U.S. population. Complementing previous research investigating how social forces such as income and social status impact its structure, we examine the role of a cognitive factor, namely, the degree of anger that individuals express towards inequality. We do so by fitting a Moderated Network Model to ISSP data, hence refining the state of the art of belief system comparison. Finally, we fill the substantive gap of this literature by *simulating* attitude change. On the grounds of the belief system literature, we investigate whether opinion change affecting central network components produces a significative variation in the overall structure of individual understanding of inequality.

We focus on the United States for two main reasons. First, because it is a country greatly affected by large economic disparities, among the highest among Western nations (Atkinson et al., 2011; Neckerman & Torche, 2007). In the U.S., the richest 10% of the population holds about 70% of all wealth, while the bottom half owns less than 2%; a gap comparable to that at the beginning of the 20th century (Chancel et al., 2022). These distributional issues are compounded by strong segregation between socioeconomic groups (Mijs & Roe, 2021) and low rates of social mobility (Hout, 2018; OECD, 2018). Second, due to its long tradition of research and a substantial body of evidence in the social justice literature. Some of the most influential academic work on people's beliefs about inequality has focused on the U.S. (e.g. Kluegel & Smith, 1981; McCall, 2013). This scholarship has shown that the U.S. public is notable for its strong belief in meritocracy (Mijs, 2018b) and relatively low support for redistribution and welfare state policies (A. Alesina et al., 2001; Hoy & Mager, 2021; Prasad, 2016). However, despite all this accumulation of evidence, little research has yet worked to understand the structure of relationships between the multiple distributional evaluations of individuals in the United States (but (Bertero et al., 2024)) and none has yet modeled attitudinal change. Both empirical and theoretical considerations make the U.S. an especially compelling context for studying the dynamics of people’s attitudes towards economic inequality.

Our contribution is structured as follows. The theory section introduces the multifaceted concept of attitudes towards inequality and summarizes key findings from two types of network approaches in social justice research. We differentiate between empirical studies that use network methods to examine how social networks influence attitudinal levels, and those that apply network methods to explore the structural organization of attitudes. The methods section details the ISSP data used, network estimation processes, and simulation procedures. In the results section, we confirm that U.S. attitudes towards inequality form an interconnected inequality belief system. This network shows a small-world structure, organized around people's belief in public redistribution and perception of income inequality. We also find significant structural variation based on individuals’ levels of anger towards inequality. Finally, we demonstrate that opinion changes in central nodes trigger substantial adaptations within the inequality belief system. We conclude by discussing the implications of our methodological and substantive contributions to the social justice and belief system literatures and propose 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 a positive or negative judgment; 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 magnitude of the distribution of resources within a society and the justice principles that shape it (Janmaat, 2013). Perceptions refer to subjective estimations about the inequality that exists (Castillo et al., 2022; Heiserman & Simpson, 2021). Instead, beliefs correspond to normative ideas about how people believe inequality should be. 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).

Since inequalities result from many social, economic, and political arrangements (McCall & Percheski, 2010), social research establishes several other fields that are highly interconnected and important for comprehending peoples’ attitudes towards inequality (McCarty & Pontusson, 2011). The way welfare states collect and distribute resources among citizens through social programs and transfers are among the main factors that determine the shape of inequality in society (Esping-Andersen & Myles, 2011; Korpi & Palme, 1998; Volscho & Kelly, 2012). Moreover, how people evaluate taxes, redistribution, and wages are topics that the literature—although unsystematically—relates 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). Therefore, to explore how people understand inequality it is essential to dig also in the subjective comprehension of the above-mentioned topics.

The literature has found various relationships between how people perceive, believe, and judge inequality, taxes, redistribution, and wages. For example, scholars showed that the individual perception of existing inequality influences normative ideas regarding how a society should be structured (Pedersen & Mutz, 2019), the belief in public redistribution (Gimpelson & Treisman, 2018; Kuhn, 2011; Kuziemko et al., 2015; Trump, 2023), and the support for progressive taxation (García‐Sánchez et al., 2020). However, there is a wide gap in understanding the associations between attitudes towards inequality in a comprehensive way. Despite research focused in explaining the association between a couple of subjective evaluations about inequality, only a few have studied them as a belief system (e.g. (Bertero et al., 2024; Franetovic & Bertero, 2023)). In these cases, a large set of indicators of distributive attitudes were used to study the underlying structure of people’s understanding of inequality. This approach provides a relevant contribution, confirming or rejecting prior associations and revealing others that were not previously considered in the social justice literature.

Besides cross-sectional investigations, scholars also engaged in the study of how individuals’ attitudes towards inequality change, without consistent results. Cruces and colleagues (2013) highlighted the importance of individuals’ perceptions of their distributional beliefs, using an experimental survey design in Argentina. Their findings show that individuals who overestimated their relative position tended to be more supportive of redistribution when informed of their true placement in the social hierarchy. Another contribution, provided by Campos-Vazquez and colleagues (2022), applied a similar experimental treatment, by providing participants with objective information about the level of income inequality and social mobility in Mexico. However, altering individuals’ perceptions of inequality did not provoke changes in their normative beliefs about income distribution, social mobility, and tax rates.

In sum, attitudes towards inequality represent a complex set of evaluations regarding economic disparities, redistribution, taxation, and wages*.* These topics are usually studied with a reductionist approach, with few attempts to link perceptions, beliefs, and judgments concurrently, as detailed by Janmaat (2013). One exception is Redmond et al. (2002), who compared the attitudes of the inhabitants of Eastern and Western countries, finding more critical views on income redistribution in the East, attributed to a larger gap in perceptions and beliefs about inequality. However, this hypothesis was not statistically tested, calling into question the effectiveness of this assertion. Additionally, García‐Sánchez et al. (2020) showed that perceptions and beliefs about inequality are not straightforwardly linked to support for public redistribution, finding that those rejecting merit-based justifications for inequality show greater willingness to redistribute, unlike their counterparts

### 2.2 A network approach to the *levels* of attitudes towards inequality

The study of subjective inequality explores how individuals perceive, understand, and explain the distribution of resources within a society. Within this field, a significant group of scholars have adopted a network approach to understanding attitudes towards inequality. These works can be classified into two main groups, depending on the variant of the network approach they adopt.

The first class focuses on how social relationships shape perceptions, beliefs, and judgments about inequality. Scholars in this area examine how network processes, such as homophily, contribute to inequality by segregating individuals into distinct socioeconomic groups. This segregation often limits exposure to diverse economic perspectives, reinforcing class divides and influencing views on inequality (Schulz et al., 2022). For example, in highly unequal societies, individuals may underestimate inequality due to a lack of exposure to varied socioeconomic realities, leading to reduced perceptions and high support for the status quo (Mijs & Usmani, 2024). On the other hand, network diversity can foster more egalitarian attitudes by connecting individuals across social classes. Studies show that inter-class relationships promote support for redistributive policies and challenge meritocratic beliefs; consequently, social ties heighten awareness of structural inequalities (García-Castro et al., 2023; Otero & Mendoza, 2024). For instance, individuals with ties to both working- and upper-class groups may develop more nuanced views on income distribution, recognizing the inequalities in opportunities and outcomes.

Additionally, network effects can amplify advantages and disadvantages, as well-connected individuals access more resources, reinforcing cumulative advantage and exacerbating inequality (DiMaggio & Garip, 2012). Geographic factors further intensify these dynamics, as physical boundaries within urban areas limit connections across different socioeconomic neighborhoods, leading to greater social fragmentation and economic divergence (Tóth et al., 2021). In sum, this type of network approach has shown that social networks have long represented a “missing link” in subjective inequality research, as the *levels* of socio-political attitudes (i.e.: the beliefs that people hold on these relevant topics) are importantly shaped by the social relationships they build in a society (Lindh et al., 2021).

### 2.3 A network approach to the *structure* of attitudes towards inequality

The second type of network approach examines the structure of attitudes towards inequality, focusing on how perceptions, beliefs, and judgments about economic disparities, redistribution, taxation and wage allocation come together 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).

However, these assumptions are challenged by the interdependent nature of socio-political attitudes (Dalege et al., 2016, 2018). Indeed, as highlighted in Section 2.1, perceptions, beliefs, and judgments about economic inequalities, redistribution, taxation, and wages are deeply interconnected. More broadly, theories of cognitive consistency (Festinger, 1957; Heider, 1946), underline that attitudes are not expressed in isolation as they are part of a broader, interdependent set of cognitions, which humans would desire to be coherent. Secondly, individuals often harbor complex, and sometimes contradictory, beliefs and perceptions about inequality, thus challenging the exchangeability of survey items. Individuals often perceive inequality as caused by both individualist and structuralist factors (Kluegel & Smith, 1981; Mijs, 2018a), and perceptions of income and wage inequalities correlate poorly when measured with different research strategies (Chambers et al., 2014; Heiserman & Simpson, 2021). Attitudes’ misalignment might result from an underlying psychological process that opposes the need for consistency. Indeed, individuals are also motivated to build *accurate* attitudes (Chaiken et al., 1989), and this can lead them to express conflictual views on a public issue.

The belief system literature incorporates cognitive consistency and accuracy as core mechanisms, where attitudes develop incrementally through associations with related beliefs (Dalege et al., 2016). For example, individuals may perceive large levels of income inequality in their country, and feel the need to judge them as fair or unfair (Time 1). Later on, they could start to associate this judgment with their belief that differences in income are high because men are advantaged in a patriarchal society (T2). Gradually, they could associate a broader number of concepts to these two, for example by thinking that if inequality is very high, this is due to politicians’ uninterest in fighting social disparities (T3), and that if sex is important in determining personal success, other characteristics such as race (T4) and religion (T5) could be important as well. While doing so, individuals would feel the need to minimize cognitive inconsistency, hence assuming coherent stances on indicators of subjective inequality (Dalege et al., 2016).

Yet, an attitude network can also show misaligned evaluations, as individuals would have to balance the need for consistency with that for accuracy. For example, individuals might think that inequality is high and that this is due to the gender pay gap; yet, they could think personal race and religion are irrelevant in the inequality equation. This process generates two distinct patterns. First, an expansion of the attitude network involves network nodes differently. Similar to what has been observed for preferential attachment (Barabási & Albert, 1999; Dalege et al., 2016), attitude components that already have strong associations with other nodes will have the highest likelihood of developing connections with newer perceptions, beliefs, and judgments about inequality (Dalege et al., 2018). Therefore, indicators differ in centrality. Secondly, misaligned and aligned evaluations must be organized to co-exist without psychological distress. Attitude networks are proposed to show high clustering to organize coherent evaluations in the same network substructure, and mismatching ones in different network areas (Dalege et al., 2019).

Researchers in this second stream of research have primarily employed two methodologies. First, scholars have used Correlational ([CCA]; Boutyline, 2017) or Relational Class Analysis ([RCA]; Goldberg, 2011) to examine variations in attitudinal structures. These techniques identify clusters of individuals who display similar correlational patterns among their beliefs, grouping people who organize associations between their views in similar ways, though not necessarily sharing the same normative positions on these topics. By analyzing the correlations between individuals’ attitudes, these algorithms investigate the similarity of their belief systems, mapping the associations between attitudes as correlational networks. For example, Kesberg and colleagues (2024) applied CCA to explore individuals’ levels of justification for political and social inequalities. System justification theory predicts that social status negatively correlates with apologism for the status quo (Jost & Van der Toorn, 2012). However, Kesberg and colleagues (2024) found that this relationship held only within one sample partition, not across the entire sample. Using RCA, DiMaggio and Goldberg (2018) demonstrated that the U.S. public organizes its attitudes towards the economic market in three main ways: the “economistic” class, which aligns with neoclassical economics and views markets as beneficial; the “hostile worlds” class, which supports markets but restricts certain morally contentious transactions (e.g., organ sales); and the “progressive” class, which endorses markets but advocates for regulatory interventions to protect public welfare and address market failures.

The second class of network methods for analyzing attitudinal structures was originally developed by Boutyline and Vaisey (2017) and has since been refined by advancements in network psychometrics (Borsboom et al., 2021) and political psychology (Brandt, 2022; Brandt et al., 2019). In this approach, attitudes are represented as nodes within weighted and signed networks, where edges indicate partial correlations between survey items (see Methods section). Franetovic and Bertero (2023) used this method to analyze attitudes towards inequality in Chile. Their results show that perceptions, beliefs, and judgments towards inequality form an integrated belief system characterized by a small-world structure. Moreover, the belief system of people from lower social exhibits higher connectivity, a network feature that predicts attitude strength (Dalege et al., 2019). Last, by combining CCA with partial correlation networks, recent work by Bertero et al. (2024) demonstrates an effective approach for addressing variations in attitudinal structures when investigating inequality belief systems. Their findings reveal that attitudes towards inequality are organized into two distinct types of belief systems in both the United States and the Netherlands. Crucially, the study shows that the organization of these attitudes significantly predicts the level of support for public redistribution.

In sum, this second strand of research has provided two key insights. First, individuals’ evaluations of issues like economic disparities, redistribution, taxation, and wages are organized within structured inequality belief systems. Second, these belief systems vary across social subgroups, with their network structures influenced by factors such as social position and cultural context. Despite this progress, the field faces two main limitations. Methodologically, researchers often rely on split-sample comparisons, which limits the ability to analyze network structures across social strata comprehensively. Additionally, there is limited understanding of how inequality belief systems might change over time, leaving important questions about their stability and evolution in response to societal shifts. Our tripartite analytical strategy attempts to address both gaps.

### 2.3 Research hypotheses

This section reviews empirical applications of network approaches to public attitudes and motivates research hypotheses. Attitudes are envisioned as networks of evaluations of attitude objects. During their formation, some nodes accumulate more connections, bridging between different areas of the network and increasing its connectivity. Networks of attitudes are clustered, to reconcile the need for both accuracy and consistency, resembling small-world networks (Watts & Strogatz, 1998). Studies have validated the small-world properties in various contexts, such as attitudes towards 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), and of political values (Turner-Zwinkels et al., 2020). More relevantly, a recent contribution has investigated the belief system encompassing attitudes towards inequality, redistribution, taxation, and wages in a drastically unequal context such as Chile (Franetovic & Bertero, 2023). Results confirm evaluations of these phenomena are organized in a single network of attitudes, which has a small-world structure. Thus, this article investigates whether perceptions, beliefs, and judgments on these topics are reunited in a belief system in the U.S., and hypothesizes:

*H1: The network of attitudes towards inequality, redistribution, taxation, and wages in the U.S. will exhibit a small-world structure.*

Attitudinal nodes will differ in importance. In social network analysis, this is often captured by measures of centrality. In a network model estimated with cross-sectional survey data, centrality measures the extent to which a given node interacts with the other variables. Importantly, the synchronic application of these methodologies does not allow the estimation of a directed network. Thus, a node can score high in centrality because (1) it strongly predicts other beliefs, (2) it is strongly predicted by other nodes, or (3) a mixture of the two (Bringmann et al., 2019). Within social justice research, the perception of large income inequality is often considered an independent variable shaping the levels of other components of attitudes towards inequality. For example, this perception influences support for redistribution (Gimpelson & Treisman, 2018; Trump, 2023), beliefs about ideal distributions (Pedersen & Mutz, 2019), and agreement with progressive taxation (García‐Sánchez et al., 2020). Complementary, scholars focusing on subjective inequality often consider the belief in public redistribution as a dependent variable. Indeed, this belief is shaped by 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), subjective national identity (Hjerm & Schnabel, 2012), and meritocratic beliefs (Mengel & Weidenholzer, 2023), among others. Moreover, the perception of inequality and the belief in public redistribution tend to correlate positively (Gimpelson & Treisman, 2018; Kuhn, 2011; Kuziemko et al., 2015; Trump, 2023) and have received large attention in the distributive justice realm due to their importance in individuals’ understandings of inequality. Indeed, Franetovic & Bertero (2023) found that in Chile, both conceptions were the most central ones in the network of peoples’ attitudes towards inequality. Therefore, the perception of income disparities and the support for redistribution are expected to emerge as central nodes of the network:

*H2: Perception of large income inequality and belief in public redistribution will be the most central nodes in the network of attitudes towards inequality, redistribution, taxation, and wages.*

The first two hypotheses investigate the attitudinal structure at the population level. However, full sample data might obscure structural heterogeneities (DiMaggio et al., 2018). Indeed, scholars have shown that the levels of attitudes towards inequality vary according to sociodemographic characteristics (Bobzien & Kalleitner, 2021; Lindh & McCall, 2020). Additionally, individuals’ social position also influences their relational structure, as the network of attitudes of people with lower levels of education, income, and social class is more densely connected (Franetovic & Bertero, 2023).

A logical extension of these findings is to investigate whether cognitive and emotional variables influence network structure. One contribution analyzed anti-Roma bias, finding that the corresponding network is highly connected for individuals with high attitude strength, and more loosely connected for individuals with lesser attitude strength (Nariman et al., 2020). This implies network connectivity relates to attitude strength (Dalege et al., 2019), and that attitude strength moderates the relationships between the network components (Haslbeck et al., 2021).

In the realm of attitudes towards inequality, scholars extensively examined the role of anger. Researchers have explored its determinants, finding U.S. citizens with lower social status tend to express higher levels of anger (Park et al., 2013). Anger is often rooted in feelings of frustration, inferiority, and injustice (Smith, 2008). Moreover, anger towards inequality also has important societal outcomes. Comparative research shows that angry individuals are unlikely to vote for parties adopting conservative stances on economic issues and express high support for economically progressive parties (Gonthier, 2023). More importantly, the link between the perceptions of existing inequalities and the willingness to engage in political action to reduce them is stronger for angry individuals (Leach et al., 2006). Anger also mediates the relationships between perceived inequalities and psychological subjective well‐being (Vezzoli et al., 2023). This research extends these investigations by assessing whether anger moderates the relationships between people’s distributive evaluations:

*H3: The structure of the network of attitudes towards inequality, redistribution, taxation, and wages is moderated by individuals’ anger towards inequality.*

Network approaches to belief systems produced a formalized theory of attitude change. Attitudes form a network where nodes differ in centrality, which measures the degree to which a node is predicted and/or predicts every other. If a change occurs in a central—rather than peripheral—node, the network of attitudes should vary to a greater extent. This has been confirmed by simulation and longitudinal studies. In simulated data, changes in central nodes have been associated with a downstream effect (Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017). This occurs when a change in the state of a node (i.e.: from “not endorsed” to “endorsed”) produces consistent adaptations in the belief system, leading other neighboring nodes to change their state. This phenomenon has also been observed, even if with lesser intensity, with longitudinal data in the field of job satisfaction (Carter et al., 2020), COVID-19-related attitudes (Chambon et al., 2022), and political beliefs (Turner-Zwinkels & Brandt, 2022). Given the lack of panel data measuring a wide set of individual-level subjective inequality indicators, this article simulates a manipulation attempt targeting each node in the network. Building on H2, this study tests whether:

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

## 3. Methods

### 3.1 Data and variables

The ISSP 2019—Social Inequality V module (ISSP Research Group, 2022) includes several indicators of subjective inequality, allowing for the modeling of attitudes towards inequality as composed of perceptions, beliefs, and judgments about inequality, redistribution, taxation, and wages (Janmaat, 2013). We analyze U.S. data, which are 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. Listwise deletion reduces the sample to 1,188 individuals. Additional analyses reveal missing cases do not impact meaningfully on the final sample. Figure 6 of the Supplemental Material shows that variables oscillate between 2% (e.g.: *Perception of large income inequality[[1]](#footnote-1)*) and 11% (*Judgment of unfair distribution*) 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. Table 1 shows the 22 selected variables and their corresponding ISSP questions. High scores indicate less tolerant attitudes towards inequality (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* (1-4) and anger towards inequality (0-10).

To cumulate with past research adopting a network approach to the study of attitudes towards inequality, the article includes twelve perceptions, seven beliefs, and three judgments about inequality in the U.S. (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, 2018a), 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, 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*, *Belief in public redistribution,* and *Belief in 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 (*Pay criteria responsibility*), or on workers’ training levels, needs, and merits (*Pay criteria training, Pay criteria need, Pay criteria 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 disinterested (*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 of multivariate data follows a multistage process (Borsboom et al., 2021). First, variables are selected based on a literature review. This ensures the resulting model validly renders the construct. Second, network estimation techniques are fitted to survey data. This article applies three types of Graphical Models that isolate the joint probability distribution of the selected variables and store them in weighted adjacency matrices. Matrices are then visualized as networks encoding conditional dependences with the presence of network edges, and conditional independences through their absence (Lauritzen, 1996). With cross-sectional data, the estimation results in an undirected network, which represents the aggregate correlational structure of the inequality belief system in the United States. Third, the toolbox of network analysis is applied to the network, describing its structural or local properties. Finally, the stability of the model parameters is assessed with bootstrapping techniques (Efron, 1979). The remainder of this section details the three estimation procedures adopted in this article and details how hypotheses are tested.

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 to have one unit of standard deviation. Then, each variable is iteratively regressed on every other, while controlling for the remaining nodes. To avoid multicollinearity issues and to increase the specificity of the model, mgm uses L1-penalized regression (LASSO) (Tibshirani, 1996). These regressions do not minimize the sum of the square deviations between the predicted values and the actual values of the target variable, as LASSO adds the tuning parameter lambda (λ) to the OLS equation. When λ is set to zero, regularization has no effect, and the model simplifies in a linear regression. As λ increases, it shrinks all estimates towards zero. Therefore, LASSO regularization induces sparsity in the network matrix, as it forces smaller coefficients to become exactly zero, effectively performing variable selection. The appropriate value of the 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 (Chen & Chen, 2008). 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 partial correlations or regression coefficients (Burger et al., 2022).

H1 and H2 are tested on the mgm network[[2]](#footnote-2). The small-worldness of the network is assessed with the test proposed by Telesford and colleagues (2011), which compares the clustering coefficient and the connectivity of the target network with those of a lattice network of the same size. The clustering coefficient of a network measures the extent to which its nodes form cliques (Watts & Strogatz, 1998). Connectivity is measured by the Average Shortest Path Length (ASPL), which is equal to the mean value of all geodesic distances[[3]](#footnote-3). A network possesses small-world characteristics if its connectivity is greater than or equal to that of the simulated random network, and if the clustering coefficient of the former is greater than that of the latter. Small-world networks produce 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. As detailed below, centrality metrics also play a critical role in testing H4. 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.

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, particularly attitudes towards inequality (see Section 2.3). CCA, for instance, is specifically designed to partition survey samples into groups of individuals who display similar patterns of correlations among attitudes. Similarly, researchers have compared the belief systems estimated on survey sub-samples with different social characteristics (e.g., income or social status) to assess how structural factors shape these networks. Alternatively, researchers have implemented the Fused Graphical Lasso, which jointly estimates two network structures to investigate group differences in edge weights (Danaher et al., 2013). Yet, all these split-sample 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 interactions and one for each three-way interaction retrieved between each pair of nodes and the moderating variable. 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[[4]](#footnote-4). 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.

These estimation types result in parameter matrices containing point estimates of the conditional associations of a dataset. Their robustness is evaluated with bootstrapping techniques (Epskamp et al., 2018). Confidence intervals around edge parameters are built with non-parametric bootstrap. For each estimated network, 10000 samples of the same size are created by sampling individuals with replacements. Edges are re-estimated in each sample, and their aggregation leads to bootstrapped confidence intervals, encapsulating the central 95% of the bootstrapped distribution. Results are shown in Figures 2 and 4 of the Supplement. The same procedure is applied to assess the robustness of the moderation effects of anger (Table 2 of the Supplemental Material). The stability of Strength centrality scores is monitored with a case-dropping bootstrap. Observations are gradually dropped from the sample and, at each step, the resulting centrality scores are verified. This allows building the Correlation Stability (CS) coefficient. This metric represents the maximum percentage of cases that can be dropped from the original sample to preserve -with 95% probability- a correlation of 0.7 between the original centrality scores and those obtained in the smaller samples. Centrality estimates are stable if the CS coefficient is greater than 0.25 or, preferably, higher than 0.50. Finally, bootstrapped difference tests are computed to directly compare two edges or strength scores. Non-overlapping bootstrapped confidence intervals are evidence of significant differences.

In summary, this article employs three types of network estimation. First, we fit the mgm to U.S. public attitudes towards inequality. This step allows us to *model* an inequality belief system as a sparse, weighted, and signed network, on which we test small-worldness and centrality metrics (H1 and H2). Building on previous findings of structural differences in belief systems across population strata, we further *estimate* how the structure of the inequality belief system changes according to individuals’ anger towards inequality. Specifically, we apply a MNM to test whether anger significantly moderates network edges (H3). Last, we employ a simplified network estimation technique, the Ising model, to *simulate* opinion dynamics, expecting changes to align with nodes’ importance within the network (H4). In the Results section, we present the outcomes of all network estimation methods and provide community detection of nodes within the inequality belief system. 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 (Golino et al., 2020). 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). In the remainder of the Methods section, we detail our simulation of attitude change.

### 3.3 Network simulation

Given the dearth of panel data on attitudes towards inequality, H4 is tested through a simulation of network dynamics. The temporal development of the network of attitudes conforms to Ising’s model (Dalege, Borsboom, Harreveld, & Maas, 2017; Ising, 1925). Nodes can assume two states (-1; +1), which originally indicate the positive or negative spin of a magnet. In the attitude domain, they represent endorsement or rejection of each survey item. Three classes of parameters regulate the overall configuration of an attitude network. The *temperature* parameter governs the entropy of the system. This variable is held constant across all simulations, as it was observed to correlate with attitude strength (Dalege et al., 2018). Two other parameters are described by the Hamiltonian function, which estimates the amount of energy expenditure of a given network configuration:

Each network node (Xᵢ to Xⱼ) is associated with a *threshold* (𝛕ᵢ to 𝛕ⱼ) indicating its predisposition to be endorsed or not. Thresholds continuously range between -1 and +1. Positive values indicate that an item is likely to be endorsed (hence assuming the state +1), and vice versa (-1). Moreover, the *ω parameter* models the strength of the interaction between each pair of network nodes. Positive values indicate positive interactions and vice versa. Configurations in which nodes characterized by positive (negative) thresholds are tied by positive (negative) edges reduce the level of energy expenditure. The Ising model encodes the central axiom of network approaches to attitudes by modeling that they strive for low energy expenditure configurations.

The simulation considers a series of successful persuasion attempts targeting one network node at a time and has been already applied to diverse socio-political attitudes (Dalege, Borsboom, Harreveld, & Maas, 2017; Schlicht-Schmälzle et al., 2018). Manipulations are operationalized as an increase in node thresholds (𝛕). The dependent variable of this simulation is the sum score of all evaluative reactions[[5]](#footnote-5), measured before and after each manipulation. H4 is confirmed if changes in the perception of large income inequality and belief in public redistribution produce downstream effects. A downstream effect occurs when the change in the state of a given node reverberates into a state change of at least one other node within the network. The simulation starts by creating 23 samples of 3000 individuals answering the 22 survey items in Table 1. Differences in the values of their responses are generated by differences set in the values of node thresholds. In the baseline condition, all nodes have a moderately negative threshold (-0.1). The other 22 samples are built by setting the threshold of one node at a time to a high value (+1), while all others maintain their moderately negative threshold (-0.1)[[6]](#footnote-6). For each of these subsamples, an attitude network is estimated, and the sum score is calculated. Finally, sum scores are compared to understand whether manipulation attempts of the same strength are associated with changes of different magnitudes in the global network structure.

## 4. Results

### 4.1 Modelling the network of attitudes towards inequality

Table 1 of the Supplemental Material provides descriptive results of the 22 attitudes. Overall, U.S. citizens perceive large disparities in economic resources, believe in a more egalitarian distribution, and judge existing inequalities as unfair. In fact, respondents tend to widely perceive a large income inequality (x̄ *=* 4.098), the tax system as regressive (x̄ = 3.642), and that the main factors related to personal success are under individuals’ control, as the items *Importance of hard* *work* and *Importance of education* have the highest means among the explanations of inequality (x̄ *=* 4.342;x̄ = 4.131). The sample firmly believes in progressive taxation (x̄*=* 4.035) and thinks both private corporations and public actors should implement policies to reduce income differences (x̄*=* 3.641;x̄= 3.272). Regarding the principles of wage allocation, respondents believe merit should be the most important regulating factor (x̄ *=* 4.327). Coherently, the U.S. public expresses critical judgments of existing inequalities and considers political actors disinterested (x̄*=* 3.997), and not capable (x̄*=* 3.982) of impacting them adequately.

**[FIGURE 1 ABOUT HERE]**

Figure 1 shows the network of attitudes towards inequality in the U.S.. Nodes of the mgm represent the 22 perceptions, beliefs, and judgments, and are colored according to the results of community detection. Edges are indicative of the unique variance shared between each item pair and are interpretable as partial correlation or regression coefficients. The network is visualized with a force-directed layout (Fruchterman & Reingold, 1991), with blue (red) weighted edges indicating positive (negative) associations, and circular shapes around each attitude displaying the portion of its variance explained by the network. Attitudes towards inequality are integrated into a single belief system in the U.S., as the network shows a single component. This means U.S. citizens can organize their beliefs about inequality, taxation, redistribution, and wages in a single mental structure. The strongest positive associations in the model are those between the *Importance of race* and *sex*, the *Importance of knowing the right people* and having good *political connections*, and the *Perception of large income inequality* and *Belief in public redistribution*. The strongest negative associations in the network are those between *Importance of hard* *work* and *giving bribes*, *the Belief in public redistribution* and *Pay criteria responsibility*, and between the *Importance of wealthy family* and *hard work*. Indeed, there are strong and positive partial correlations between perceiving individuals’ race and sex (bootstrapped[[7]](#footnote-7) x̄ = 0.359; bootstrapped CI = 0.302, – 0.423) and knowing the right people and having political connections (x̄ = 0.331; CI = 0.287, 0.387) as important factors for determining personal success. In the same vein, those who hold strong perceptions of income inequality are more likely to believe in public redistribution (x̄ = 0.331; CI = 0.287, 0.387). Importantly, respondents seem at least partially able to differentiate between individualist and structuralist explanations of inequality, as they perceive either *hard work* or *giving* *bribes* (x̄ = -0.115; CI = -0.182, -0.058), or *hard work* and *wealthy family* to be important sources of social and economic inequalities (x̄ = -0.047; CI = -0.092, -0.001). Moreover, supporting public redistribution increases the likelihood of rejecting a job’s responsibility as an acceptable pay criterion (x̄ = -0.051; CI = -0.094, -0.012).

The description of these edges highlights two patterns that are found in the network of attitudes towards inequality. First, most of the associations are positive in sign. Considering that U.S. citizens express on average critical levels of attitudes towards inequality, this first pattern entails that their large perceptions, egalitarian beliefs, and severe judgments are also coherently organized. A second pattern lies in network nodes that are most likely to be strongly connected. Indeed, Figure 1 shows that the strongest partial correlations link variables tapping the same conceptual domain. This is evident when observing the edges between *Pay criteria responsibility* and *Pay criteria merit,* and between *Pay criteria responsibility* and *Pay criteria training*,and when considering the associations linking the ten explanations of inequality (variables from *Importance of wealthy family* to *Importance of sex* of Table 1, and located in the bottom part of Figure 1).

However, some important exceptions are found concerning this second pattern. First, not all explanations of inequality correlate with the same intensity. On top of the negative associations discussed above (between *work-bribes*, and *work-wealthy family*), it is important to observe the segregation of three structuralist explanations of inequality (*Importance of religion, race,* and *sex*), which are much more likely to interact with themselves rather than with the other perceptions, beliefs, and judgments in the model. This entails that individuals endorsing one of these three perceptions are more likely to consider the other two factors as important sources of inequality, rather than believing in the relevance of individualist determinants such as hard work or personal education. Moreover, strong associations can also emerge across conceptual domains. This is the case of the aforementioned association between the *Perception of large income inequality* and the *Belief in public redistribution*, and this also occurs for the positive association between the *Perception of tax regressivity* and the *Belief in progressive taxation* (x̄= 0.281; CI = 0.224; 0.334). Finally, not all nodes whose survey questions are semantically similar, or belong to the same class of attitudes towards inequality vehemently correlate. For example, believing in a person’s *need* as a just pay criterion is largely unrelated to endorsing *merit* (x̄ = -0.002; CI = -0.016, 0.016), or *responsibility* (x̄ = -0.002; CI = -0.013, 0.013).

These associations produce four network communities. The explanations of inequality are grouped into structuralist, individualist and mixed factors. The structuralist community (yellow) encompasses the importance of societal divisions in the generation of inequalities, such as *race*, *religion*, and *sex*. The individualist community (green) groups explanations of inequality related to individuals’ action, such as their *hard work* or their achieved *education*, and *train*, *responsibility*, and *merit* as pay criteria. The mixed community (blue) gathers meso-level explanations of inequality, related to people’s social contexts, such as the importance of *knowing the right people*, *having political connections* or *coming from a wealthy family*. Finally, the red community groups together all judgments, all perceptions, and the *beliefs in public* and *private redistribution.*

Node predictability gives information on the extent to which the variance of a given variable is captured by the network model. The R2 scores vary greatly across nodes. Pay criteria show the lowest predictability (R2*Pay criteria need* = 0.159, R2*Pay criteria merit* = 0.164, R2*Pay criteria training* = 0.170, R2*Pay criteria responsibility* = 0.200). These variables are the least embedded in the network structure, and this means their levels are likely to be influenced by additional variables excluded from the model. Conversely, the *Perception of large income inequality* and the *Belief in public redistribution* display the highest R2 (0.463 and 0.500 respectively). This result was anticipated by discussing the strong connections these nodes have with the others. Their high scores speak in favor of the validity of the variable selection procedure, as variables that are central to the literature on attitudes towards inequality are also well-described in the network model.

Figure 1 is used to test weather perceptions, beliefs, and judgments on inequality expressed by the U.S. public are organized into a single belief system. Furthermore, the belief system theory predicts the inequality belief system is organized with a small work structure (H1). This would occur as individuals are prompted to balance their needs for accuracy and consistency. At a structural level, the network of attitudes towards inequality shows low density, as only 30.6% of possible network edges are retrieved by the network estimation procedure. When modeled as an unweighted network, ASPL scores 1.801, and the clustering coefficient is equal to 0.447. The estimated network has a higher ASPL and lower clustering coefficient than a simulated random network of the same size. Hence, H1 is confirmed, as the network has a small-world score of 0.228.

Our second expectation is that the *Belief in public redistribution* and the *Perception of large income inequality* are the most central nodes in the inequality belief system. Figure 2 shows standardized Strength centrality scores. Z-scores help to compare this metric across the full-scale and Ising networks. Strength is a direct function of the magnitude of nodes’ connections. Thus, variables that are strongly and/or frequently connected to other nodes have the highest scores. Raw values range between 0.506 and 1.271. We confirm the *Belief in public redistribution* and the *Perception of large income inequality* are the most central nodes in the network (raw scores of 1.271 and 1.141 respectively) and also across all bootstrapped samples (bootstrapped mean centrality scores of 1.146 and 1.278). Bootstrapped difference tests reveal their scores are not significantly different (CI*Belief in public redistribution-Perception of large income inequality* = -0.060, 0.328), although *Belief in public redistribution* is more central than all other nodes (CIBelief in public redistribution-Importance of wealthy family = -0.437, -0.123), and the *Perception of large income inequality* is significantly more important than all nodes below *Belief in progressive taxation* in Figure 2 (CI*Perception of large income inequality-Belief in progressive taxation* = -0.407, -0.049). Centrality estimates are remarkably stable, as the CS coefficient scores 0.75. This means dropping as much as 75% of cases from the original sample would preserve a correlation of 0.7 between the original centrality scores and those obtained in the reduced sample. Figures 1 and 2 show the four pay criteria and the belief in market redistribution are peripheral to the network. The same occurs for the *belief in market redistribution*. This shows that highly endorsed items are not necessarily central nodes of the network of attitudes: although the mean of attitudes towards *market redistribution* (x̄ = 3.641) is higher than that of *public redistribution* (x̄ = 3.272), the former is peripheral to the network, whereas the latter is the most central node.

[FIGURE 2 ABOUT HERE]

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

Figure 1 assumes attitudes towards inequality are organized in the same way in all population strata. However, we hypothesized that anger towards inequality moderates the structure of the inequality belief system (H3). Figure 3 shows the results of the MNM, which clearly confirm H3. Each panel represents the result of a network estimation performed at a fixed level of anger towards inequality. Layouts are determined by averaging the results of the force-directed algorithm of each network. Anger is represented as a disconnected and white node to highlight its special status in the model. The magnitudes of moderation effects are reported in Table 2 of the Supplemental Material, which also shows the proportion of time an effect is found across the bootstrapped samples. Overall, more than 25 network edges are strongly moderated by anger towards inequality. Results are robust to bootstrapping techniques, as these effects are retrieved in more than 83% of the derived samples.

[FIGURE 3 ABOUT HERE]

The strongest moderation effect is equal to 0.064 and involves the pairwise relationship between the *Judgment of failure of public redistribution* and the *Belief in public redistribution.* This triadic relationship can be interpreted as in standard regression analysis, with the exception that dependent and independent variables can be inverted. When anger equals zero, an increase of a unit of *Belief in public redistribution* produces an increase of 0.025 units of *Judgment of failure of public redistribution*, and vice versa. As the moderation effect is positive, the higher the anger towards inequality, the stronger the relationship between *Belief in public redistribution* and *Judgment of the failure of public redistribution*. When anger scores 3 (top right panel of Figure 3) the relationship grows to 0.217. In the other two panels, the edge *Belief in public redistribution* *- Judgment of failure of public redistribution* has a magnitude of 0.473 and 0.665. This moderation means that anger towards inequality makes the association between the belief in public redistribution and the judgment on its failure stronger. Note that this association was null in the model (ω = 0). The exploration of three ways interactions shows this relationship is instead very strong, but only for individuals who are angry towards inequality.

Other strong moderation effects regard the relationships between the explanations of inequality*.* On the one hand, increasing levels of anger are associated with reduced boundaries between the endorsement of individualist, structuralist, and mixed explanations of inequality. When anger equals zero, perceiving a *wealthy family* as an important factor for getting ahead in life increases the likelihood of considering *sex* as important, and vice versa (ω = 0.065). When anger equals ten, an increase of one unit in the belief of the importance of a *wealthy family* increases the belief in the importance of personal *sex* of 0.475 units. In the same fashion—when anger is zero—perceiving the importance of a *wealthy family* is weakly related to believing in the importance of having good *political connections* (ω = 0.145). However, for those who reported the maximum levels of anger, this relationship became stronger (ω = 0.465). On the other hand, the relationships between other explanations of inequality are negatively moderated by anger, meaning that the endorsement of structuralist explanations reduces the likelihood of believing in individualist ones, and vice versa. In the mgm of Figure 1, the perceptions of the importance of *parental education* and the importance of *race* are not associated (ω = 0). However, when anger equals ten, an increase of one unit on the item *Importance of parental education* is associated with a decrease of 0.300 of the variable *Importance of race*, and vice versa. Similarly, the perceptions of the importance of personal *education* and giving *bribes* are weakly and negatively associated when anger is low (ω=-0.018) and became strongly opposed when anger scores its maximum (ω*=*-0.418).

Another strong moderation effect regards the *Importance of education* and the *Belief in market redistribution*. When anger is zero, believing in the importance of personal education is weakly predictive of the belief in market redistribution (ω = 0.009). This relationship is much stronger when anger equals ten (ω= 0.269). Note that this moderation entails that nodes’ importance in the network can change dramatically when considering the role of the cognitive variable. For individuals who do not experience anger towards inequality, the *belief in market redistribution* is a peripheral variable (see Figure 2), whose variance is only marginally captured by the model (Figure 1). However, when individuals are angry, the *belief in market distribution* interacts more firmly with the other nodes, becoming more central in the network of perceptions, beliefs, and judgments about inequality.

Finally, some moderation effects also involve pay criteria. For example, an increase of one point in the *perception of large income inequality* increases the belief in *merit* as a just allocation principle of only 0.010 units, when anger is equal to zero. A variation of the same entity of *Perception of large income inequality* would produce an increase in *merit*’s levels of 0.043, 0.087, and 0.120 units when anger scores 3, 7, and 10.

These patterns impact on network communities. At low levels of anger (top panels of Figure 3), we observe the same communities of the full sample network (Figure 1). Yet, when anger increases, the inequality belief systems are organized into lesser communities. Indeed, the bottom panels of Figure 3 shows that at high levels of anger towards inequality the U.S. public hold belief systems with three communities. The main differences relate to the explanations of inequality, which became part of a single community. This suggest anger pushes U.S. citizens to perceive an increased number of individual and structural factor to be important in determining social inequalities.

The description of these moderation effects introduces two important findings relative to the structure of the network of attitudes towards inequality. When anger is low, the estimated networks show lower mean edge absolute values and a low number of negative associations. For example, when anger towards inequality scores 0 and 3, the networks of attitudes have mean absolute edge weights of 0.061 and 0.068, and only 46 and 59 associations are negative in sign. When anger scores 7 and 10, the mean absolute edge weight is 0.101 and 0.127, and the number of negative edges grows to 62 and 63. Thus, a higher level of anger produces tighter associations in the belief system and drives individuals to further differentiate some perceptions, beliefs, and judgments from one another, organizing them in a potentially contentious way.

### 4.3 Simulating attitude change

Since nodes differ in centrality, changes in important nodes could produce larger readjustment processes than those triggered by changes in peripheral ones. To test for this, full-scale variables are dichotomized, and an Ising simulation is implemented. Table 1 of the Supplemental Material shows descriptives of the dummy variables. Figure 4 plots the resulting network (top panel) and the strength centrality of each node (bottom one).

[FIGURE 4 ABOUT HERE]

Contrary to Figure 1 and Figure 2, the edges of Figure 4 represent regularized logistic regression coefficients. The layout of the network replicates that of Figure 1, to improve the comparability between the full and reduced-scale network estimation. The Ising network has a similar density to the full-scale one (density = 0.32). Moreover, the strongest edges of Figure 1 remain the most important in the Ising model. Indeed, the strongest associations in the networks are those between the *Importance of race* and *sex*, *Perception of tax regressivity* and *Belief in progressive taxation*, *Importance of political connections* and *Importance of giving bribes*, *Perception of large income inequality,* and *Belief in public redistribution*. Therefore, strength scores are consistent, as well as network communities. The bottom panel of Figure 4 shows that the *Perception of large income inequality*, *Importance of race*, and *Belief in public redistribution* are the most central nodes, whereas pay criteria and the *Belief in market redistribution* are the most peripheral ones.

Figure 1 in the Supplemental Material compares the standardized centrality scores that each node totalizes in the two models. The plot confirms the ranking is subject to marginal variations only, with the position of the node *Belief in public redistribution* being the most important exception (it is the most important node in the full-scale network, the third in the Ising one). As for the mgm network, the point estimates of the strength scores of the most important nodes of the Ising network do not statistically differ. Indeed, the nodes *Perception of large income inequality*, *Importance of race*, *Belief in public redistribution,* and *Importance of wealthy family* have raw centrality scores of 5.819, 5.131, 4.473, and 4.076 respectively. Bootstrap tests reveal overlapping CIs for many of these differences[[8]](#footnote-8). Yet, *Perception of large income inequality* and *Belief in public redistribution* are more central than the majority of other nodes. The score of the former is significantly higher than those of nodes below the *Importance of wealthy family* in the centrality table of Figure 4[[9]](#footnote-9); the score of the latter is higher than those of nodes below the *Importance of political connections*[[10]](#footnote-10). The CS coefficient is remarkably high also for these estimates (0.75). Finally, the small-world test is applied to the Ising network to ensure the robustness of the result discussed above. The test outputs a small-world score of 0.223, in line with the score of the full-scale network. These results confirm *Perception of large income inequality* and the *Belief in public redistribution* are the most important nodes of the inequality belief system, which display small-world characteristics, regardless of modeling strategies.

[FIGURE 5 ABOUT HERE]

H4 predicts a change in these central nodes will produce downstream effects, which means we expect an opinion change related to these attitudes to trigger wider readjustments in the inequality belief system. We test for this through simulated manipulation attempts targeted at each network node. Manipulations are modeled as an increased value of the threshold of the targeted node (from 𝛕 = -0.1 to 𝛕 = +1), while keeping the others fixed at a moderately negative value (𝛕 = -0.1). Note that according to the Hamiltonian function, reported in the method section, the change in the threshold of a given node is not automatically reflected in the change of its state. Indeed, nodes are embedded in the network of attitudes, and their state is also dependent on the ω parameter. This means that changing 𝛕 from -0.1 to 𝛕 = +1 only increases the probability that a given node will assume the state +1. However, this is a probabilistic prediction rather than a mechanical one. For example, a node with 𝛕 = +1 could become negatively linked with other nodes, and this can in turn exercise pressure on it to remain in the negative state.

Results are shown in the forest plot of Figure 5, which presents the network sum scores obtained after each manipulation. When all thresholds are set to a moderately negative value (𝛕 = -0.1), the network sum score is -5.462 (CI = -5.721, -5.203). This synthetic index represents a moderately negative configuration of attitudes towards inequality, as the dependent variable of the simulation ranges between -22 (all items are rejected) to 22 (all items are endorsed). The reference line on the left of Figure 5 discerns between successful and unsuccessful manipulation attempts. All dots have confidence intervals on the right of the dashed reference line, meaning each simulated manipulation induced a significant change in the network sum score. The dotted reference line of Figure 5 helps to detect downstream effects, as it is positioned 2 units on the right of the former. Nodes whose confidence intervals are on the right of the line produced downstream effects, as their manipulation produced their state change, and also induced wider readaptation processes in the network of attitudes towards inequality.

Eight nodes produce changes that are bigger than two units. These nodes are the *Perception of large income inequality* (x̄ = -2.135; CI = -2.388, -1.882), *Importance of race* (x̄ = -2.301; CI = -2.564, -2.038), *Belief in public redistribution* (x̄ = -2.425; CI = -2.685, -2.165), *Perception of tax regressivity* (x̄ = -2.570; CI = -2.826, -2.314), *Belief in progressive taxation* (x̄ = -2.623; CI = -2.884, -2.360), *Judgment of failure of public redistribution* (x̄ = -2.673; CI = -2.928, -2.418), and the Importance of *coming from a wealthy family* and personal *sex*. This confirms and extends H4. A comparison between Figure 5 and the centrality table of Figure 4 reveals that Strength centrality and magnitude of sum score change are highly correlated. Indeed, nodes whose manipulation produces downstream effects cover the highest position in the centrality table. The only exceptions to this pattern is the node *Judgment of failure of public redistribution* and the *Importance of sex*, which have medium strength centrality, but still produce huge variations in the network when targeted. The simulation shows that, regardless of the nodes’ importance, manipulation of a single item is not enough to produce drastic variation in the network. Indeed, across all manipulations, the sum scores representing the overall levels of attitudes towards inequality remain negative in sign.

## 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, 2018a). 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.(A. Alesina & Glaeser, 2004; McCall, 2013; Shariff et al., 2016). This was also captured in ISSP survey data, where this item is the most endorsed[[11]](#footnote-11). 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 (A. Alesina et al., 2001; A. F. 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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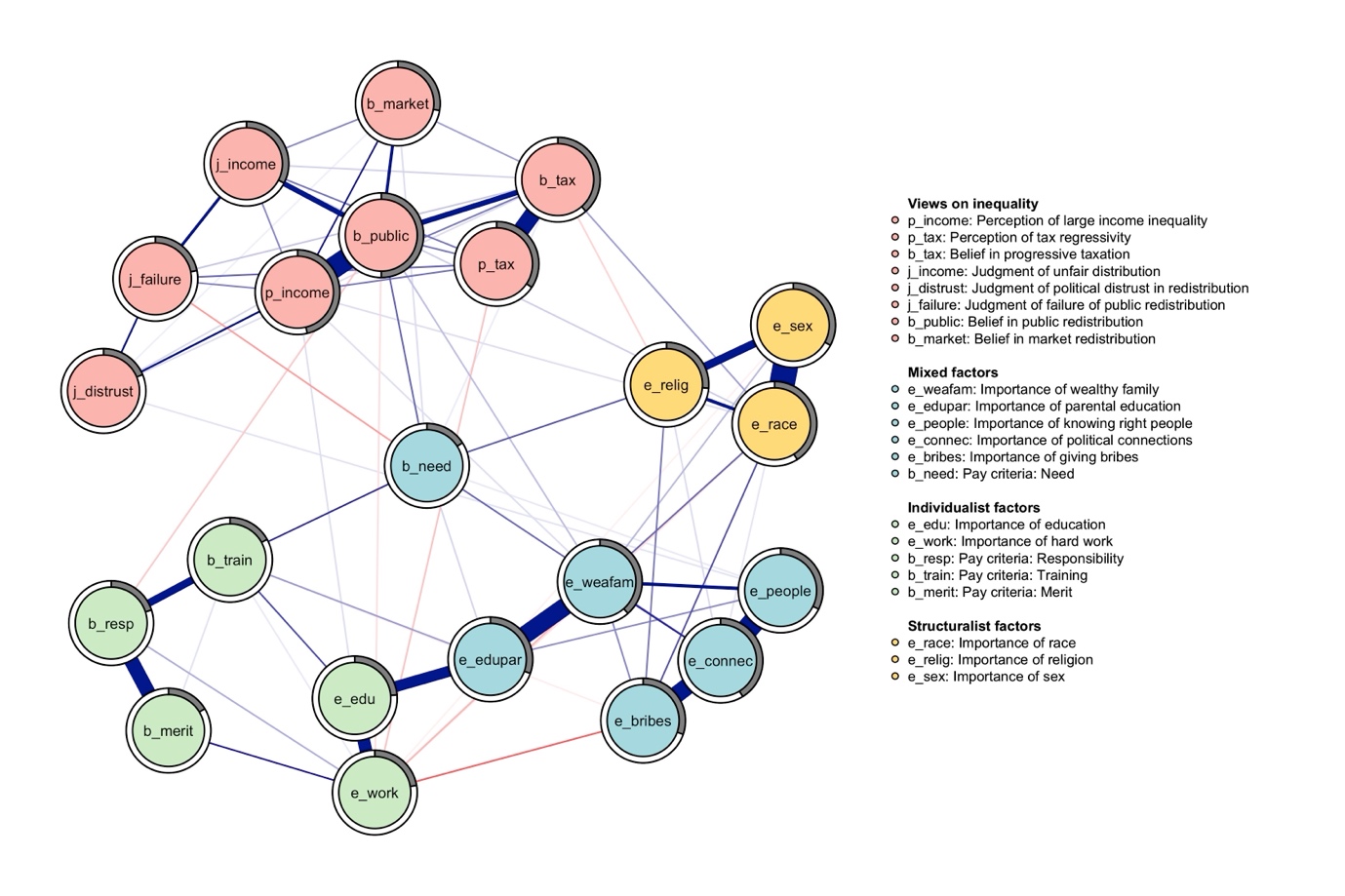
# V. Tables and Figures

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 |

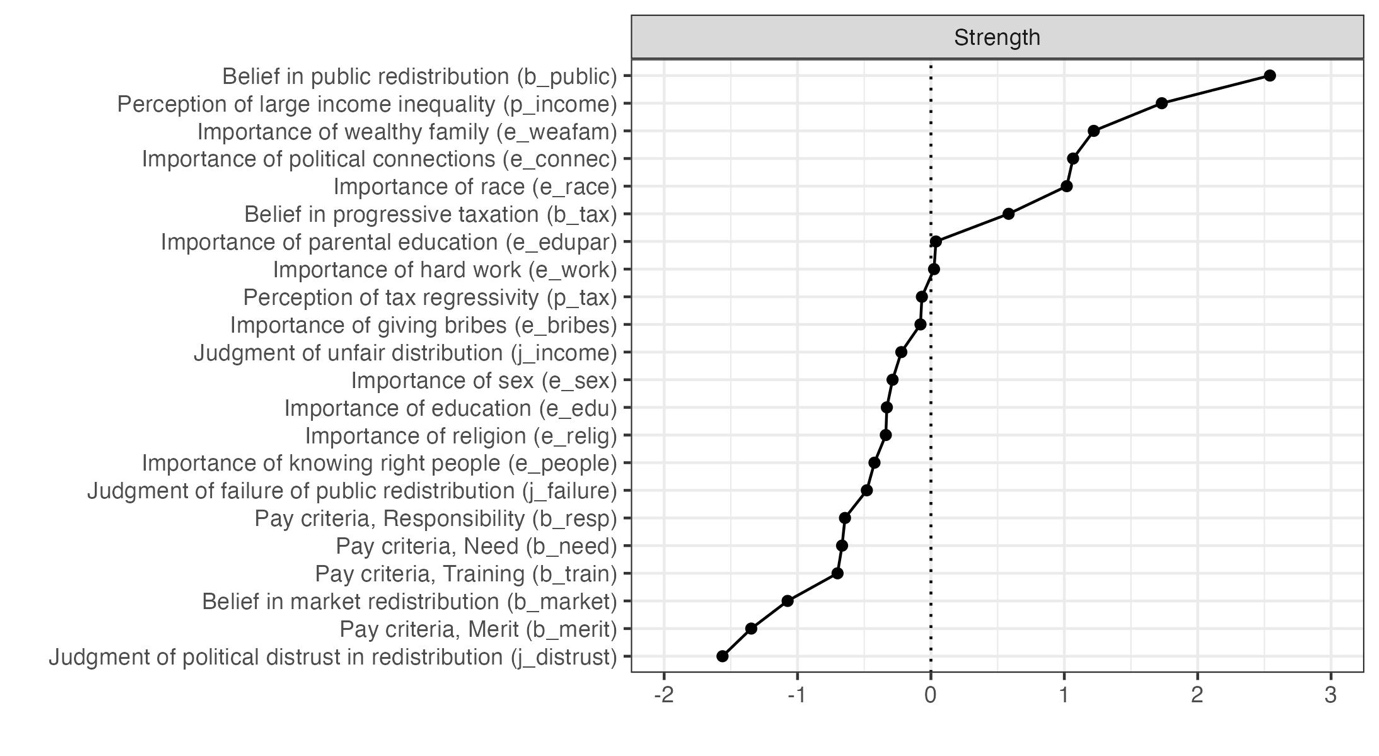
*Caption:* Squared brackets indicate common prompts between different items. The polarity of asterisked variables was inverted to have maximum values aligned with high perception, egalitarian beliefs, and critical judgments of existing inequality.

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



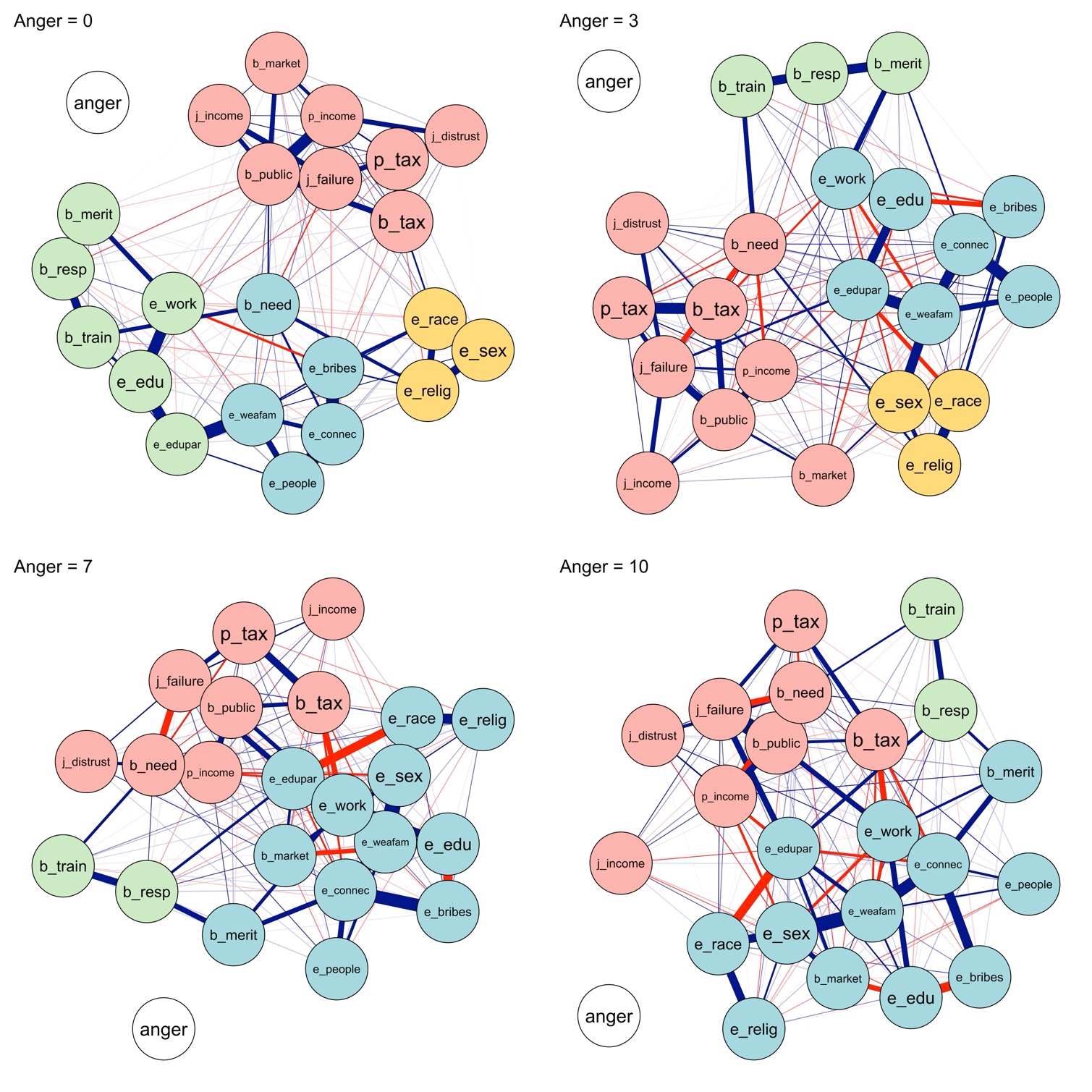
*Caption:* The network of attitudes towards inequality. Variables are represented as nodes, which are connected by weighted and signed edges. Nodes are colored according to their theoretical classification in perceptions, beliefs, and judgments about inequality. The circular shape around each node plots 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



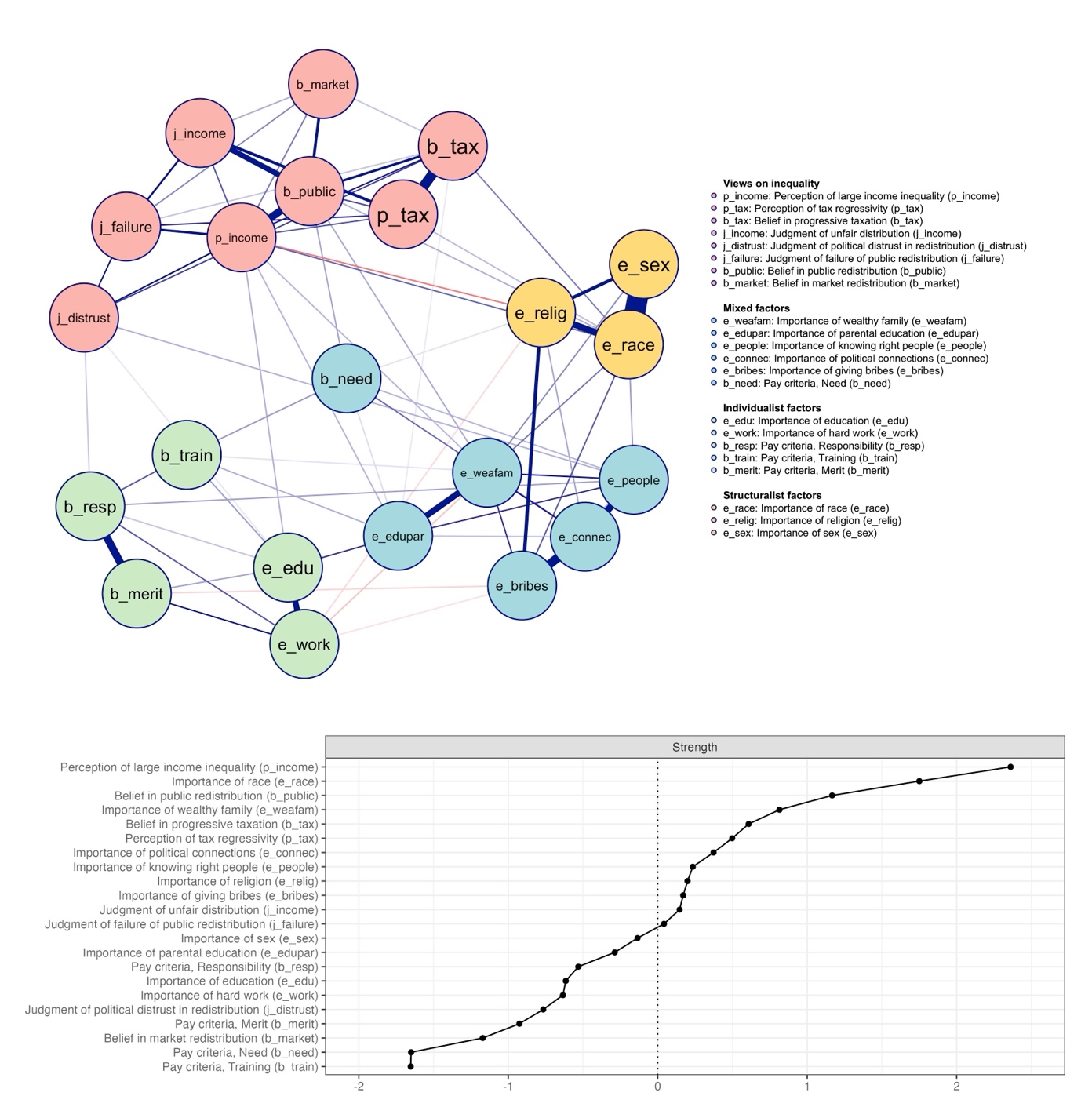
*Caption:* Strength centrality of GGM’s nodes. Each row shows one node and its centrality, measured in z-scores.

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



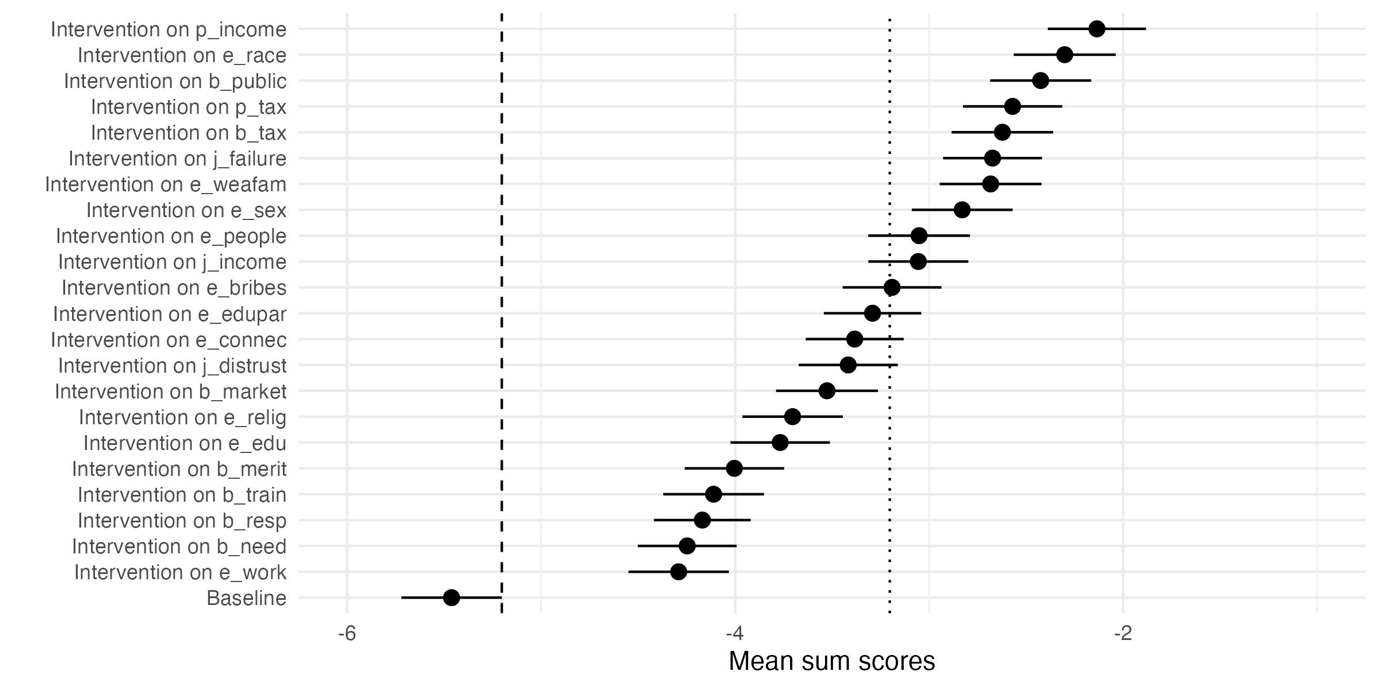
*Caption:* Each panel shows the result of a GGM estimation at a fixed level of the moderating variable, anger. Nodes are colored according to their classification in perceptions, beliefs, and judgments. Anger is plotted in white for clarity. Weighted and signed edges indicate conditional associations. 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. As a robustness check, H1 and H2 are also tested on the binary network (see Results section). [↑](#footnote-ref-2)
3. To cumulate with past research, the clustering coefficient and the ASPL are calculated from the absolute and unweighted adjacency matrix. [↑](#footnote-ref-3)
4. 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-4)
5. 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-5)
6. 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-6)
7. Throughout the article the magnitude of network edges is described by the mean value of the parameters scored across all bootstrapped samples. Reference to the point estimates of the parameters are indicated with ω instead*.*  [↑](#footnote-ref-7)
8. CI*Perception of large income inequality-race*= -1.835, 1.121; CIPerception of large income inequality-Belief in public redistribution= -2.102, 1.072; CIBelief in public redistribution-race = -1.142, 1.552; CIBelief in public redistribution-Importance of wealthy family = -2.157, 0.32. [↑](#footnote-ref-8)
9. CIPerception of large income inequality-Importance of wealthy family = -2.938; -0.055. [↑](#footnote-ref-9)
10. CIBelief in public redistribution-connec = -2.583; -0.146. [↑](#footnote-ref-10)
11. Respondents indicated it has an importance of 4.342 on a five-point scale (See Table 1 in the Supplemental Material). [↑](#footnote-ref-11)