

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

II. Abstract and keywords

This article explores the growing field of subjective inequality, addressing the 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 *model* attitudes towards economic inequality as a belief system, which is a network of interacting cognitive evaluations, that reveals a small-world structure. Central to this network are the perception of income inequality and support for public redistribution. Additionally, we *estimate* how anger towards inequality impacts this belief system, using a moderated network model to demonstrate that anger significantly influences nearly one-third of the network's ties. Lastly, by *simulating* changes in attitude, we find that modifications at the network's central nodes lead to more significant overall shifts than those at its periphery. This comprehensive approach provides nuanced insights into the complex dynamics of public opinion on inequality.

Keywords: Attitude network; Belief systems; Attitudes toward 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).

However, research on distributive justice is characterized by two limitations. First, the disparate perceptions, beliefs, and judgments composing the construct of attitudes toward inequality have been analyzed unsystematically (Janmaat, 2013). Researchers working in this field have usually focused either on a single dimension of this construct or on a limited number of indicators per dimension, neglecting important interactions between a larger set of cognitive evaluations of this phenomenon. Moreover, research has often been impeded by a reductionist approach, where attitudes toward inequality are studied in isolation from those related to taxation, redistribution, and wages (Franetovic & Bertero, 2023). Secondly, social justice research has long investigated the *levels* of these attitudes (the endorsement by individuals), while neglecting the cognitive structure in which they are embedded. Indeed, attitudes are not held in isolation, they are embedded in a belief system (Converse, 2006). The inquiries on the *structure* of attitudes toward inequality complement those carried out with

standard approaches and shift the focus from the normative stances individuals assume on inequality to how these are packed together to form a belief system (Brandt & Sleegers, 2021; Dalege et al., 2016).

This article addresses these shortcomings by using an attitude network approach to study attitudes toward inequality in the United States, one of the countries where social disparities are most visible and impactful (Wilkinson & Pickett, 2009). The increasing levels of concentration of income and wealth (Piketty & Saez, 2014), are accompanied by a rise in socioeconomic segregation throughout different scenarios of social life in the United States during recent decades (Mijls & Roe, 2021). Likewise, Americans are characterized by a significant mismatch between the sustained increase in economic inequality and their limited and ambivalent support for redistributive policies (Wright, 2018), commonly explained by a strong perception of meritocracy and social mobility (A. Alesina & Glaeser, 2004; Shariff et al., 2016). All these distributive elements make it a country of great interest, which has received tremendous academic attention within the field of social justice research 4/25/24 11:00:00 AM. However, to date, there is a lack of a holistic and systemic approach capable of understanding how the wide range of Americans' attitudes toward inequality are structured and related to each other.

To explore how attitudes towards inequality are structured in the U.S., we craft a tripartite analytical strategy. First, we *model* attitudes toward inequality as a network of interconnected cognitive evaluations regarding inequality, redistribution, taxation, and wages. The network approach to attitudes improves the understanding of how they are structured in the U.S., allowing for the discovery of interactions that are usually hidden by the adoption of a latent variable framework. Second, we *estimate* the different configurations the attitude network can assume within the population. In particular, the role of anger toward inequality is investigated to show how different levels of emotional attachment to this issue prompt individuals to organize their cognitions differently. Finally, the network approach is exploited to *simulate* attitude change. On the grounds of the belief system literature, we investigate whether opinion change affecting central -versus peripheral- network components produces wider variation in the belief system.

Our contribution is structured as follows. The theory section reviews the most important findings gathered by social justice research on attitudes toward inequality. Later, the network approach to attitudes is discussed. The methodological section describes the data and variables, the network estimation processes, and the simulation procedure. Results show how attitudes toward inequality, redistribution, taxation, and wages are structured in the U.S., how their configuration varies by levels of anger, and how attitude change reverberates across the network. In the discussion, these findings are compared with those produced by the literature on social justice and attitude networks. Finally, the conclusions highlight the main contributions of this research and its limitations, while suggesting avenues 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 toward the object is represented by the sum of the responses to each statement, or by some weighted combination of these scores.

Particularly, attitudes toward inequality represent a multidimensional 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 toward 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; K. 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. One of the most researched is the one between perceptions and beliefs about inequality. Scholars showed that the individual perception of existing inequality influences normative ideas regarding how a society should be structured. This phenomenon, known as the anchoring effect, describes how people adjust their expectations according to their perceptions (Pedersen & Mutz, 2019). Another commonly found association is between the perception of inequality and the belief in public redistribution (Gimpelson & Treisman, 2018; Kuhn, 2011; Kuziemko et al., 2015; K. Trump, 2023), a positive relation particularly significant among people who perceive themselves to be at the top of the social ladder (Fatke, 2018) and who reject beliefs that justify inequality (García-Sánchez et al., 2020). Indeed, people's subjective social positions (Brown-Iannuzzi et al., 2015), and their explanations of inequality (Fong, 2001) have been

established as even more important than people's objective position in shaping their support for redistribution. Finally, the belief in progressive taxation has been also related to how people perceive inequality (García-Sánchez et al., 2020).

Besides cross-sectional investigations, scholars also engaged in the study of how individuals' attitudes toward 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 (Campos-Vazquez et al., 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 toward inequality are a complex and multidimensional issue often 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. Nevertheless, a significant gap remains in the literature regarding the internal structure of these attitudes. Franetovic and Bertero (2023) recently made a noteworthy advance with their study on Chile, incorporating perceptions, beliefs, and judgments simultaneously through an attitude network approach. Their research reveals that all people's views on inequality, redistribution, taxation, and wages are part of a unique and interconnected network of attitudes, and that individuals from lower socioeconomic status systematically present more multidimensional structures of understanding. We

seek to advance our understanding of attitudes toward inequality as a network, taking the United States as a case study, a country with high economic inequality and a long tradition in distributive justice research.

2.2 A network approach to attitudes toward inequality

In the field of attitude research, the latent variable model has long been a cornerstone for understanding attitudes toward complex social issues like inequality. It posits attitudes are latent constructs -unmeasurable properties or tendencies within a person- that manifest through observable behaviors, affective responses, and cognitions (Eagly & Chaiken, 1993; Rosenberg, 1960). Therefore, responses to specific survey items are believed to be caused by the latent attitude (Bagozzi, 1981; Bagozzi & Burnkrant, 1979). Yet, this model faces criticism, especially its assumptions of local independence and exchangeability (Dalege et al., 2016, 2018; Fazio, 2007). Local independence suggests that once the latent attitude is accounted for, the observable indicators do not influence each other (Bollen, 1989). The exchangeability assumption speculates that increasing the number of measurement items of a construct merely improves reliability, without providing new information (Bollen & Lennox, 1991).

These assumptions are challenged by the interconnected and dynamic nature of socio-political attitudes, particularly concerning inequality. Firstly, attitudes tapping different dimensions of social inequalities meaningfully interact. For example, high perceptions of economic inequalities decrease the perception that economic differences are produced by individuals' merit (Kuhn, 2019), which contradicts the notion of local independence. Moreover, perceptions and beliefs about inequality co-occur in determining the individual levels of support for public redistribution (García-Sánchez et al., 2020). 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, 2018), 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. Therefore, a shift toward models that acknowledge the reciprocal influences and the cognitive and social dynamics at play is warranted.

The Causal Attitude Network [CAN] model has been recently introduced as an alternative to latent variable models (Dalege et al., 2016, 2018, 2019). Central to this approach is the notion that the correlations observed between indicators of the same attitude are not the by-products of a latent factor but are meaningful and indicative of their direct influence. CAN models an attitude as a network composed of the cognitive evaluations of the attitude object, and their causal associations. The limitations of the latent model discussed directly map into CAN's assumptions. This model specifies cognitive consistency and the need for accuracy as key mechanisms for attitude formation and dynamics. Attitudes are formed through incremental aggregation of different evaluations of the same attitude objects. For example, individuals may observe the 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).

An application of the CAN model is valid when it features measures of all dimensions of the construct (Dalege et al., 2016; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017; Dalege et al., 2019). Hence, its application to attitudes toward inequality would require studying perceptions, judgments, and beliefs about inequality. Yet, limiting the analysis to inequality is reductive, as other attitude objects such as taxation and redistribution are evaluated interdependently (e.g.: Trump, 2023; Volscho & Kelly, 2012). Therefore, this article builds on the CAN model but necessitates a wider theoretical approach. Rather than examining how multiple evaluations of the same attitude objects interact to form an attitude network, this paper explores how perceptions, beliefs, and judgments about inequality, redistribution, taxation, and wages coalesce in a belief system. Belief systems are configurations of ideas and attitudes that are bound together by cognitive and social constraints (Converse, 2006). The concept of a belief system scales up the reasoning underlying the CAN model, suggesting that attitudes are not held in isolation. To back his theory, Converse computed pairwise correlations between a wide set of Northern American political attitudes, showing that people often hold inconsistent attitudes, unless they are highly interested in politics. Recent contributions have refined the theory and methodologies proposed by Converse. On the one hand, the theory was formalized to account for network dynamics. Belief systems are defined as networks of attitudes exerting causal influence on each other, while being subject to the influence of external social phenomena, such as political communication and peer pressure (Brandt & Sleegers, 2021). Scholars

have shown that this theory can predict the magnitude and location of attitude change in a belief system (Turner-Zwinkels & Brandt, 2022).

On the other hand, scholars have started to adopt network models in which edges are indicative of plain (Boutyline & Vaisey, 2017) or partial correlations (Brandt et al., 2019) between attitudes measured with survey data. Both options converge in demonstrating that political belief systems are built around political identities and show that their structure is influenced by educational and political interest levels. However, methodological studies have shown that although nodes are theorized to interact causally, the standard estimation techniques are not able to isolate individual-level causality flows. Indeed, the great majority of scholars operating in this field tend to fit network models to cross-sectional attitudinal data. Depending on the network estimation strategies, the edges of this model represent the raw (Boutyline & Vaisey, 2017), or the unique variance (Brandt et al., 2019; Dalege et al., 2016) shared between each item pair. Yet, cross-sectional network estimation only gives insights into the between-person structure of a belief system (Brandt & Morgan, 2022). Practically, this means that these studies estimate a single network model, whose parameters represent the average values found in the sample. Thus, when addressed with this approach, belief systems are societal rather than individual-level constructs (Martin, 2000). Finally, the theoretical argument that attitudes causally interact -which is admittedly evident in the acronym of the CAN model- can not be extended to the interpretation of findings produced by empirical work applying network models to cross-sectional data. Indeed, this estimation strategy outputs an undirected network where item associations are symmetrical, thus being inadequate to model causality (Neal et al., 2022).

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 toward political

candidates (Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017; Dalege et al., 2016) post-national citizenship identities (Schlicht-Schmälzle et al., 2018), job satisfaction (Carter et al., 2020), bio-based plastic (Zwicker et al., 2020), and of political values (Turner-Zwinkels et al., 2020). More relevantly, a recent contribution has investigated the belief system encompassing attitudes toward 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 toward inequality, redistribution, taxation, and wages will show a small-world structure in the U.S.

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 toward inequality. For example, this perception influences the considerations on the legitimacy of income differentials (Trump, 2018), the desired magnitude of inequalities (Faggian et al., 2023), and -although indirectly- support for public redistribution (García-Sánchez et al., 2018). 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; K. 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 toward inequality. Therefore, the evaluations of income disparities and the belief in the importance of 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 toward 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. Indeed, scholars have shown that the levels of attitudes toward inequality vary according to sociodemographic characteristics (Bobzien & Kalleitner, 2021; Lindh & McCall, 2020). Additionally, social status 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 toward 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 toward 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 the components of attitudes toward inequality:

H3: The structure of the network of attitudes toward inequality, redistribution, taxation, and wages is moderated by individuals' anger toward 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 in the attitude networks (Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017). The downstream effect occurs when a change in the state of a node (i.e.: from “not endorsed” to “endorsed”) produces consistent adaptations in the network, 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.

3. Method

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 toward 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 generated between 2% (e.g.: *ineq_p¹*) and 11% (*ineq_j*) 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 selected variables and their corresponding ISSP question. High scores indicate high perceptions of inequalities, egalitarian beliefs, and judgments of unfairness about existing levels of social disparities. All variables are measured on a 1 to 5 scale, with the exceptions of *ineq_j* (1-4) and anger toward inequality (0-10).

To cumulate with past research adopting a network approach to the study of attitudes toward 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 perceptions of large income inequality (*ineq_p*) and tax regressivity (*reg_p*). The analyses include ten explanations of inequality, also known as inequality beliefs (Mijs, 2018), which are items asking respondents to indicate how important they perceive a set of structural and individual factors to be for getting ahead in life (*family-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 (*prog_b*), and public and private redistribution (*redis_p*, *redis_m*). 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 (*resp*), or on workers' training levels, needs, and

¹ In the remainder of the article, network nodes are indicated in italics.

merits (*train*, *need*, *merit*). Finally, respondents judged the fairness of the existing income distribution in the U.S. (*ineq_j*), the extent to which politicians are disinterested (*redis_d*), and unsuccessful (*redis_f*) in addressing and fighting inequality.

[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 attitudes toward inequality 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 toward 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, R^2 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 network². 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 distances³. 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). Although different metrics can be computed, research suggests avoiding the application of other conventional centrality conceptualizations to graphical models of this kind. Measures such as betweenness or closeness rely on assumptions that are often violated in a network where nodes do not have agency (Bringmann et al., 2019).

² As a robustness check, H1 and H2 are also tested on the binary network (see Results section).

³ To cumulate with past research, the clustering coefficient and the ASPL are calculated from the absolute and unweighted adjacency matrix.

H3 investigates whether the network structure estimated on the full sample hides structural heterogeneities that are produced by different levels of anger toward 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). 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). These procedures are impeded by two shortcomings. First, data-split approaches reduce sample size, and thus statistical leverage; second, these strategies can only model a step moderation process, where the slope of a relationship can differ between two groups, but not within them. The Moderated Network Model (MNM) mitigates both problems (Haslbeck et al., 2021). Its edges are estimated with the same strategy outlined above, relying on a set of regularized linear regressions whose tuning parameter is obtained by minimizing the EBIC. However, in each of these regressions, the MNM adds a moderation effect of a selected variable. Therefore, MNM produces two parameter matrices, one for the pairwise 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 toward 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' dichotomization⁴. 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.

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.

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 CIs are evidence of significant differences.

3.3 Network simulation

Given the dearth of panel data on attitudes toward 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:

$$H(x) = -\sum_i \tau_i x_i - \sum_{i,j} \omega_{i,j} x_i x_j$$

Each network node (X_i to X_j) is associated with a *threshold* (τ_i to τ_j) 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 reactions⁵, measured before and after each manipulation. H4 is confirmed if changes in the perception of large income inequality and belief in progressive taxation 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. For each of these subsamples, an attitude network is estimated, and the sum

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).

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).

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 toward inequality

Table 1 of the Supplemental Material provides descriptives 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 perceive income inequality as very high, the tax system as too regressive ($\bar{x}_{ineq_p} = 4.098$; $\bar{x}_{reg_p} = 3.642$), and that the main factors related to personal success are under individuals' control, as the items *work* and *edu* have the highest means among the explanations of inequality ($\bar{x}_{work} = 4.342$; $\bar{x}_{edu} = 4.131$). The sample firmly believes in progressive taxation ($\bar{x}_{prog_b} = 4.035$) and thinks both private corporations and public actors should implement policies to reduce income differences ($\bar{x}_{redis_m} = 3.641$; $\bar{x}_{redis_p} = 3.272$). Regarding the principles of wage allocation, respondents believe merit should be the most important regulating factor ($\bar{x}_{merit} = 4.327$). Coherently, the Northern American public expresses critical judgments of existing inequalities and considers political actors disinterested ($\bar{x}_{redis_d} = 3.997$), and not capable ($\bar{x}_{redis_f} = 3.982$) of impacting them adequately.

[FIGURE 1 ABOUT HERE]

Figure 1 shows the network of attitudes toward inequality in the U.S. Nodes of the mgm represent the 22 perceptions, beliefs, and judgments, and are colored according to membership to these categories. 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 explained variance. Attitudes toward 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 *race* and *sex*, *people* and *connec*, and *ineq_p* and *redis_p*. The strongest negative associations in the network are those between *work* and *bribes*, *redis_p* and *resp*, and between *family* and *work*. Indeed, there are strong and positive partial correlations between perceiving individuals' race and sex (bootstrapped⁷ $\bar{x}_{race-sex} = 0.359$; bootstrapped CI = 0.302, 0.423) and knowing the right people and having political connections ($\bar{x}_{people-connec} = 0.331$; CI = 0.287, 0.387]) as important factors for determining personal success. In the same vein, those who hold critical perceptions of income inequality are more likely to believe in public redistribution ($\bar{x}_{ineq_p-redis_p} = 0.331$; CI = 0.287, 0.387). Importantly, respondents seem at least partially able to differentiate between individualist and structuralist explanations of inequality, as -on the one hand- they perceive either hard work or bribes ($\bar{x}_{work-bribes} = -0.115$; CI = -0.182, -0.058), or -on the other hand- hard work and coming from a wealthy family, to be important sources of social and economic inequalities ($\bar{x}_{work-family} = -0.047$; CI = -0.092, -0.001). Moreover, believing in public redistribution increases the likelihood of rejecting a job's responsibility as an acceptable pay criterion ($\bar{x}_{redis_p-resp} = -0.051$; CI = -0.094, -0.012).

The description of these edges highlights two patterns that are found in the network of attitudes toward inequality. First, most of the associations are positive in sign. Considering that U.S. citizens express on average critical levels of attitudes toward 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 *resp* and *merit*, and between *resp* and *train* (e.g.: the pay criteria), and when considering the associations linking the ten explanations of inequality (variables from *family* to *sex* of Table 1, bottom right corner nodes in Figure 1). However, some important exceptions are found concerning this second pattern. First, not all explanations of inequality correlate with the same

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.

intensity. On top of the negative associations discussed above (between *work-bribes*, and *work-family*), it is important to observe the segregation of three structural explanations of inequality (*relig*, *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 (*ineq_j-redis_p*), and this also occurs for the positive association between the perception of tax regressivity and the belief in progressive taxation ($\bar{x}_{reg_p-prog_b} = 0.281$; CI = 0.224; 0.334). Finally, not all nodes whose survey questions are semantically similar, or belong to the same dimension of attitudes toward inequality vehemently correlate. For example, believing in a person's need as a just pay criterion is largely unrelated to endorsing the meritocratic principle ($\bar{x}_{need-merit} = -0.002$; CI = -0.016, 0.016), or the responsibility one ($\bar{x}_{need-resp} = -0.002$; CI = -0.013, 0.013). Yet, Figure 1 shows that cross-dimensional associations can be considerably strong. For example, the belief in public redistribution is strongly associated with other judgments (e.g.: *ineq_j*) and perceptions (e.g.: *ineq_p*).

Node predictability gives information on the extent to which the variance of a given variable is captured by the network model. The R^2 scores vary greatly across nodes. Pay criteria show the lowest predictability ($R^2_{need} = 0.159$, $R^2_{merit} = 0.164$, $R^2_{train} = 0.170$, $R^2_{resp} = 0.200$). 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, *ineq_p* and *redis_p* display the highest R^2 (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 toward inequality are also well-described in the network model. At a structural level, the network of attitudes toward 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. H1 is confirmed, as the network has a small-world score of 0.228.

Centrality gives insight into nodes' importance in the network. Figure 2 shows standardized strength centrality scores. Z-scores help 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. 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 ($CI_{redis_p-ineq_p} = -0.060, 0.328$), although *redis_p* is more central than all other nodes ($CI_{redis_p-family} = -0.437, -0.123$), and *ineq_p* is significantly more important than all nodes below *prog_b* in Figure 2 ($CI_{ineq_p-prog_b} = -0.407, -0.049$). 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. Therefore, point estimates and bootstrap analyses confirm H2. Figures 1 and 2 show the four pay criteria and the belief in market redistribution are peripheral to the network. The nodes *resp*, *need*, *train*, and *merit* have weak connections in the network, and their R^2 are very low. 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 levels of attitudes toward market redistribution ($\bar{x}_{redis_m} = 3.641$) are higher than those of public redistribution ($\bar{x}_{redis_p} = 3.272$), 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 toward inequality

Figure 1 assumes attitudes toward inequality are organized in the same way in all population strata. However, cognitive variables such as anger toward inequality might produce different attitudinal configurations. To test H3, a MNM is fitted to ISSP data. Results are visualized in Figure 3. Each panel represents the result of a network estimation performed at a fixed level of anger toward 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, H3 is confirmed, as more than 25 network edges are strongly moderated by anger toward 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 *redis_f* and *redis_p*. 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 *redis_p* produces an increase of 0.025 units of *redis_f*, and vice versa. As the moderation effect is positive, the higher is anger toward inequality, the stronger the relationship between *redis_p* and *redis_f*. When anger scores 3 (top right panel of Figure 2) the relationship grows to 0.217. In the other two panels, the edge *redis_p* - *redis_f* has a magnitude of 0.473 and 0.665. This moderation means that anger toward 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 ($\omega = 0$). The exploration of three ways interactions shows this relationship is instead very strong, but only for individuals who are angry toward inequality.

Other strong moderation effects regard the relationships between the explanations of inequality *family* and *sex*, *family*, and *connec*, *edupar* and *race*, and *edu* and *bribes*, ($M = 0.06, 0.06, -0.05$, and -0.05 respectively). Two patterns emerge. On the one hand, increasing levels of anger are associated with reduced boundaries between the endorsement of individualist and structuralist 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 ($\omega_{family-sex} = 0.065$). When anger equals ten, an increase of one unit in the belief of the importance of a rich 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 connections ($\omega_{family-connec} = 0.145$). However, for those who report the maximum levels of anger, this relationship became stronger ($\omega_{family-connec} = 0.465$). 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 good parental education and personal race are not associated ($\omega_{edupar-race} = 0$). However, when anger equals ten, an increase of one unit on the item *edupar* is associated with a decrease of 0.300 of the variable *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 ($\omega_{edu-bribes} = -0.018$) and became strongly opposed when anger scores its maximum ($\omega_{edu-bribes} -0.418$).

Another strong moderation effect regards *edu* and *redis_m*. When anger is zero, believing in the importance of personal education is weakly predictive of the belief in market redistribution ($\omega = 0.009$). This relationship is much stronger when anger equals ten ($\omega_{edu-redis_m} = 0.269$). 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 toward 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 *ineq_p* would produce an increase in *merit*'s levels of 0.043, 0.087, and 0.120 units when anger scores 3, 7, and 10.

The description of these moderation effects introduces two important findings relative to the structure of the network of attitudes toward 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 toward 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, an increased level of anger produces tighter associations in the belief system and prompts individuals to organize their perceptions, beliefs, and judgments in a potentially conflictual 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 *race* and *sex*, *reg_p* and *prog_b*, *connec* and *bribes*, *ineq_p*, and *redis_p*. Therefore, strength scores are consistent. The bottom panel of Figure 4 shows that *ineq_p*, *race*, and *redis_p* are the most central nodes, whereas pay criteria and *redis_m* 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 *redis_p* 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 *ineq_p*, *race*, *redis_p*, and *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 differences⁸. Yet, *ineq_p* and *redis_p* are more central than the majority of other nodes. The score of the former is significantly higher than those of nodes below *family* in the centrality table of Figure 4⁹; the score of the latter is higher than those of nodes below *connec*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 *ineq_p* and *redis_b* are the most important nodes of the network of attitudes, which display small-world characteristics, regardless of modeling strategies.

[FIGURE 5 ABOUT HERE]

To test H4, simulated manipulation attempts are performed. Manipulations are modeled as an increased value of the threshold of the targeted node (from $\tau = -0.1$ to $\tau = +1$), while keeping the others fixed at a moderately negative value ($\tau = -0.1$). 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 $\tau = +1$ 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 $\tau = +1$ could become

⁸ $CI_{ineq_p-race} = -1.835, 1.121$; $CI_{ineq_p-redis_p} = -2.102, 1.072$; $CI_{redis_p-race} = -1.142, 1.552$; $CI_{redis_p-family} = -2.157, 0.32$.

⁹ $CI_{ineq_p-family} = -2.938; -0.055$.

¹⁰ $CI_{redis_p-connec} = -2.583; -0.146$.

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. When all thresholds are set to a moderately negative value ($\tau = -0.1$), the network sum score is -5.462 (CI = -5.721, -5.203). This synthetic index represents a moderately negative configuration of attitudes toward 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 4 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 4 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 toward inequality. Eight nodes produce changes that are bigger than two units. These nodes are *ineq_p* ($\bar{x} = -2.135$; CI = -2.388, -1.882), *race* ($\bar{x} = -2.301$; CI = -2.564, -2.038), *redis_p* ($\bar{x} = -2.425$; CI = -2.685, -2.165), *reg_p* ($\bar{x} = -2.570$; CI = -2.826, -2.314), *prog_b* ($\bar{x} = -2.623$; CI = -2.884, -2.360), and *redis_f* ($\bar{x} = -2.673$; CI = -2.928, -2.418). 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 exception to this pattern is the node *redis_f*, which has medium strength centrality, but still produces 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 toward inequality remain negative in sign.

5. Discussion

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

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

Within this network, the strongest associations involve the explanations of inequality, the perception of large income inequality, and the belief in public redistribution. Results showed that perceiving personal sex as a key variable for personal success is highly predictive of considering religion and race as important, and vice versa. In the same fashion, explanations pointing at the individual agency, such as the role of hard work, and personal and parental education are strongly tied in the network. Although researchers have long distinguished between individualist and structuralist explanations of inequality (also referred to as “inequality beliefs” or “stratification beliefs”) (Kluegel & Smith, 1981), most of these perceptions correlate positively empirically (Mijs, 2018). Consistently, most of the associations between these two kinds of explanations were positive. The only exception to this pattern regards the belief in the importance of hard work, which contrasts with considering bribes, coming

from a wealthy 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 endorsed¹¹. 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. F. 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; K. Trump, 2023). Furthermore, perceived inequality is even more important than objective inequality in predicting redistributive preferences across contemporary societies (Bussolo et al., 2021; K. 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 toward 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

¹¹ Respondents indicated it has an importance of 4.342 on a five-point scale (See Table 1 in the Supplemental Material).

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 toward 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 toward 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 toward 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 toward 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 toward 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 toward 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 toward 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 toward 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 toward 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 toward inequality are influenced by objective measures of social stratification. Since their levels were also known to be influenced by anger toward 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).

IV. References

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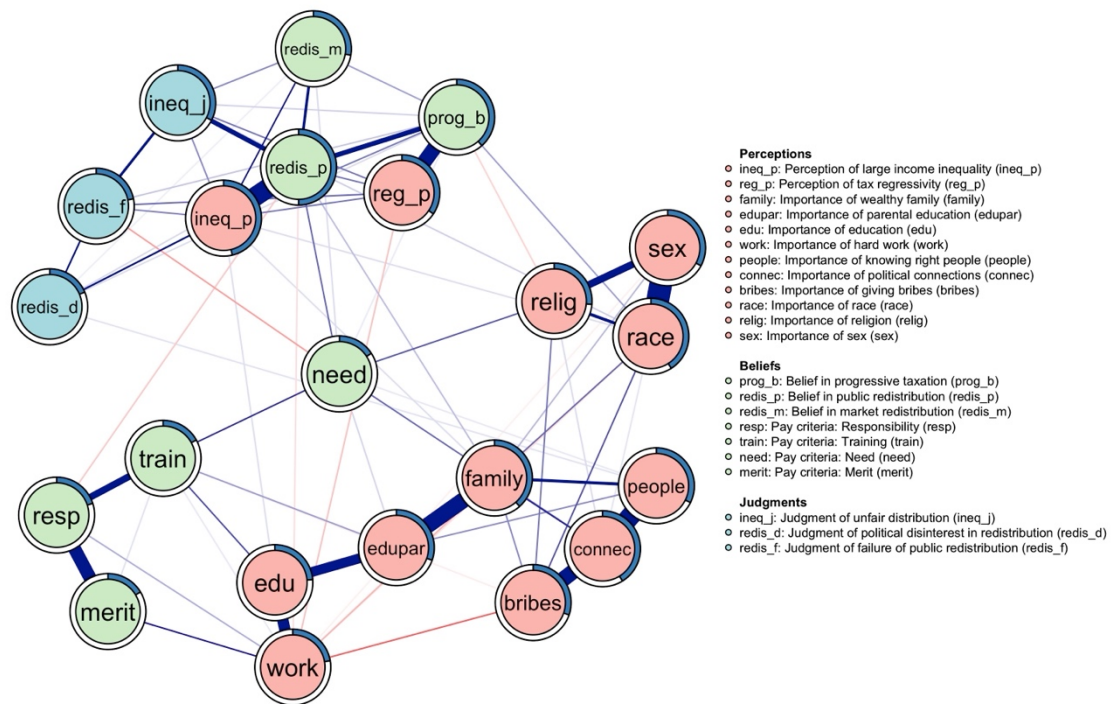
V. Tables and Figures

Table 1: Labels and survey questions

Label	Question	Type
ineq_p	To what extent do you agree or disagree with the following statement: Differences in income in the U.S. are too large. *	Perception
reg_p	Generally, how would you describe taxes in the U.S. today for those with high incomes?	Perception
family	[How important is] coming from a wealthy family [for getting ahead in life?] *	Perception
edupar	[...] having well-educated parents [...] *	Perception
edu	[...] having a good education yourself [...] *	Perception
work	[...] hard work [...] *	Perception
people	[...] knowing the right people [...] *	Perception
connec	[...] having political connections [...] *	Perception
bribes	[...] giving bribes [...] *	Perception
race	[...] a person's race [...] *	Perception
relig	[...] a person's religion [...] *	Perception
sex	[...] being born a man or a woman [...] *	Perception
prog_b	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
redis_p	It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes. *	Belief
redis_m	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
resp	[How important do you think that ought to be in deciding pay?] How much responsibility goes with the job *	Belief
train	[...] The number of years spent in education and training. *	Belief
need	[...] Whether the person has children to support. *	Belief
merit	[...] How well he or she does the job. *	Belief
ineq_j	[...] How fair or unfair do you think the income distribution is in the U.S.?	Judgment
redis_d	[...] 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
redis_f	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

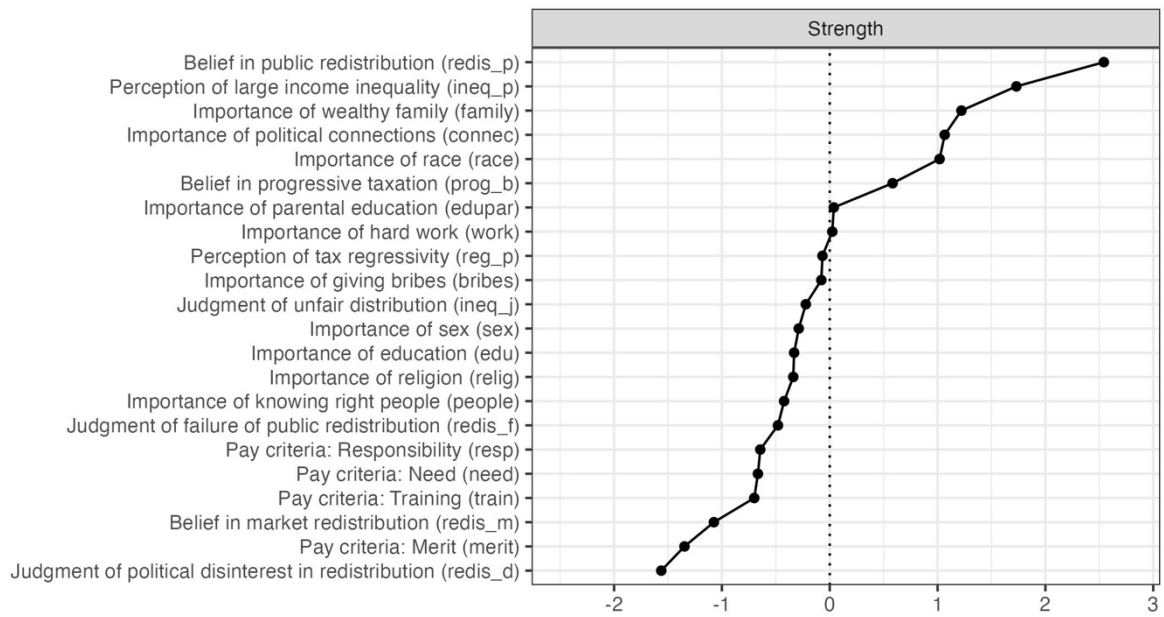
Caption: Squared brackets indicate common prompts between different items. The polarity of asterisked variables was inverted to have maximum values aligned with high perception, egalitarian beliefs, and critical judgments of existing inequality.

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



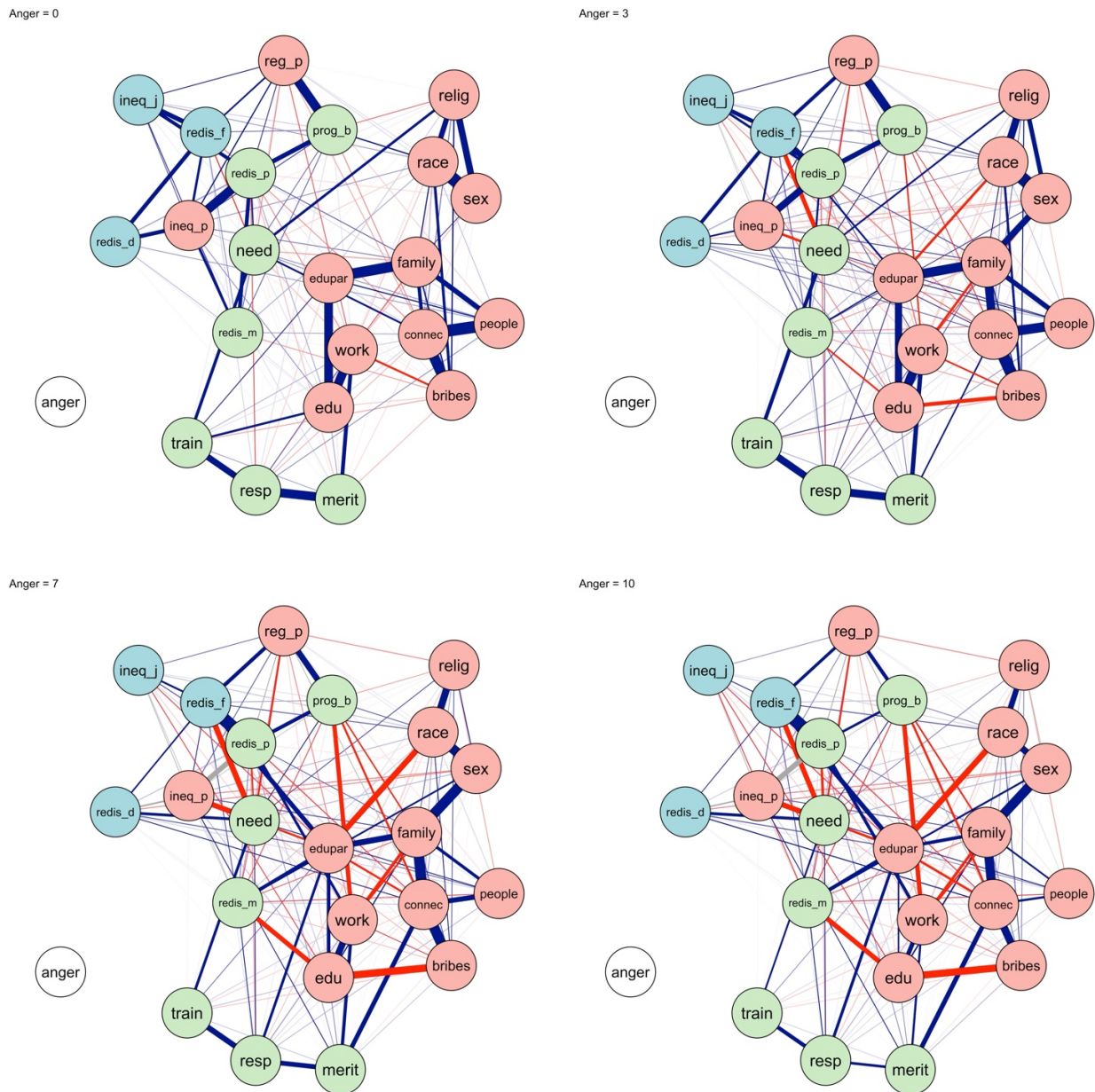
Caption: the network of attitudes toward inequality. Variables are represented as nodes, which are connected by weighted and signed edges. Nodes are colored according to their theoretical classification in perceptions, beliefs, and judgments about inequality. The circular shape around each node plots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



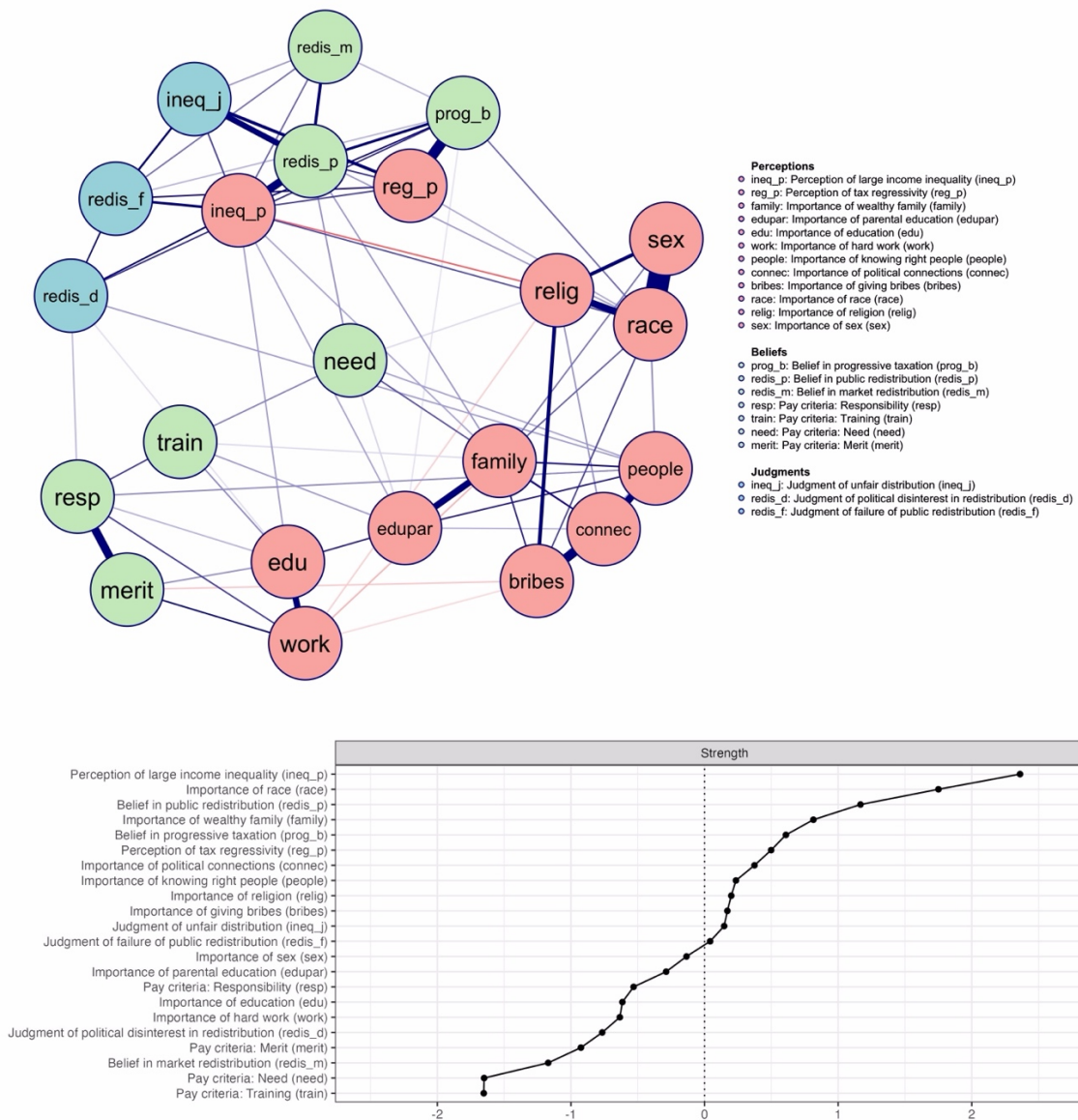
Caption: Strength centrality of GGM's nodes. Each row shows one node and its centrality, measured in z-scores.

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



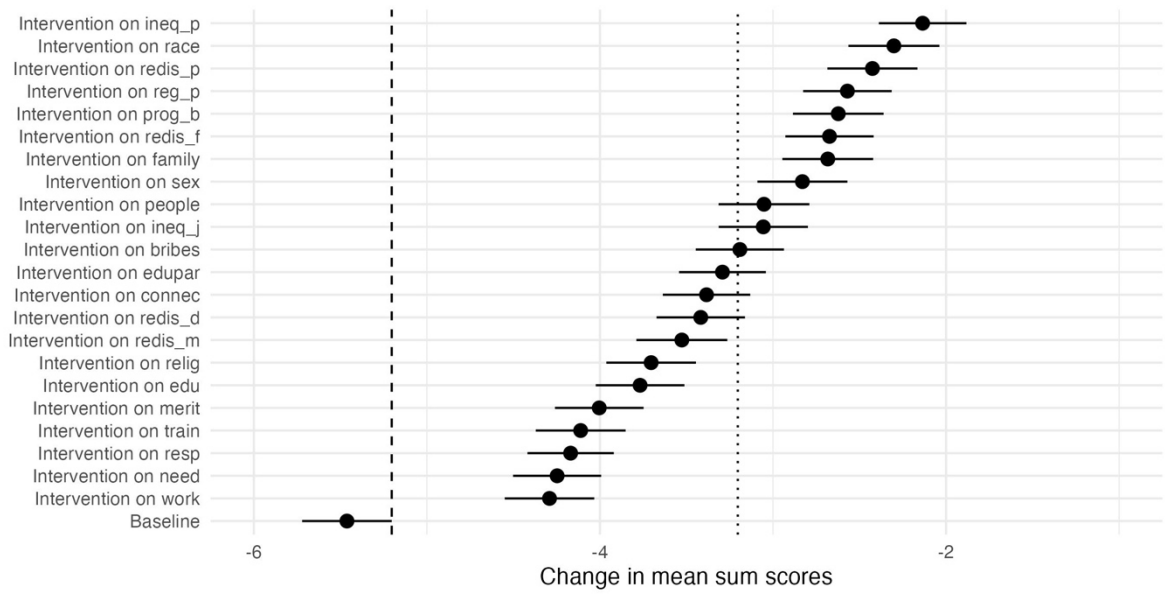
Caption: each panel shows the result of a GGM estimation at a fixed level of the moderating variable, anger. Nodes are colored according to their classification in perceptions, beliefs, and judgments. Anger is plotted in white for clarity. Weighted and signed edges indicate conditional associations.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

Figure 4: Ising Model - Network of attitudes toward 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.