# Modeling, estimating, and simulating: formalizing attitudes towards inequality as a complex network

## Abstract

## 1. Introduction

## 2. Theory

## 2.1 Attitudes towards inequality in the U.S.

### Definition

### Literature in the us

### But what is missing is a network approach + study of dynamics

## 2.2 A network approach to the study of attitudes towards inequality

### Few words on the latent variable model

### A network approach to attitudes

### CAN

### Better belief system

## 3. Method

## 3.1 Data and variables

Studying attitudes towards inequality with a holistic approach requires a wide variety of indicators. The ISSP 2019 – Social Inequality V module (ISSP Research Group, 2022) offers this possibility, as it includes questions concerning perceptions, beliefs, and judgments about inequality, taxation, and redistribution. This paper uses 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 1852 individuals. After listwise deletion, we work with a subsample of 1,188 individuals for the network estimations and simulation. Additional analyses reveal missing cases do not impact meaningfully on the final sample. Figure 7 of the Supplement shows that variables generated between 2% (e.g.: *ineq\_p*) and 11% (*ineq\_j*) of missing cases. Thus, nonresponses were fairly distributed between the selected variables. Moreover, Table 3 of the Supplement shows that the means of the variables do not significantly differ between the original sample and the reduced one.

Following the operationalization proposed by (Janmaat, 2013), we account for the multidimensionality of attitudes towards inequality by measuring it through perceptions, beliefs, and judgments. Considering the close relationship between inequality, taxation, and redistribution, we use evaluative reactions in all three domains. Table 1 shows the selected variables and their corresponding ISSP question. We uniform the polarity of each variable to have high values indicating larger perceptions, egalitarian beliefs, and judgments of unfairness about existing levels of inequality. All variables are measured on a 1 to 5 scale, with the exceptions of ineq\_j (1-4) and anger towards inequality (0-10).

### Describe perceptions

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 perceptions of high-income inequality (*ineq\_p*) and of tax regressivity (*reg\_p*). The analyses include ten 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*).

### Beliefs

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 in public and private redistribution (*redis\_p, redis\_m*). Moreover, one survey battery tapped 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 merits (*train, merit, need*).

### Judgments

Finally, respondents judged the fairness of the existing income distribution in the U.S. (*ineq\_j*), the political willingness to address inequality (*redis\_d*), and the level with which governmental actions fought the issue (*redis\_f*).

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 meritocratic beliefs, high perception, and critical judgments of existing inequality.

## 3.2 Network estimation

### The general process of estimation (from data to robustness)

Network estimation of multivariate data follows a multistage process (Borsboom et al., 2021). First, variables are selected on the grounds of a literature review. This ensures resulting models validly render the construct under scrutiny. Second, network estimation techniques are fitted to survey data. This step depends on the data type. This article applies Graphical Models, which encode the joint probability distribution of the selected variables in a weighted adjacency matrix. The matrix is then represented as a network that encodes conditional dependences with the presence of network edges, and conditional independences through their absence (Lauritzen, 1996). With cross-sectional data, network estimation results in an undirected network, which represents the aggregated correlational structure of attitudes towards inequality in the U.S. Third, the toolbox of network analysis is applied to the network, to describe its structural or local properties. As a final step, the stability of the model’s parameters is assessed with bootstrapping techniques (Efron, 1979). As Graphical Models differ in how they estimate model parameters, the remainder of this section details the estimation procedures adopted in this article, and details how hypotheses are tested.

### mgm estimation (here also small world and centrality)

To address H1 and H2, a Mixed Graphical Model (mgm) is estimated (Haslbeck & Waldorp, 2020). This model can accommodate variables measured on different scales and estimates the model’s parameters through a loop of node-wise regularized linear regressions. At the beginning of the analysis, variables are mean-centered and re-scaled to have one unit of standard deviation. Then, each variable is iteratively regressed on each other, while controlling for every other node of the model. To avoid multicollinearity issues and to increase the specificity of the model, mgm uses regularized regressions.

The regularization technique of choice is the l1-penalized regression (LASSO) (Tibshirani, 1996). Unlike linear regression, the goal of regularized regression is not to find the coefficients that minimize the sum of squared differences between the predicted values and the actual values of the target variable. In LASSO regularization, an additional penalty term is introduced. The tuning parameter lambda (λ) controls the amount of regularization applied. When λ is set to zero, LASSO regularization has no effect, and the model is mathematically equivalent to a linear regression. As λ increases, the penalty term becomes more significant, and it shrinks the coefficient estimates toward zero. Therefore, LASSO regularization induces sparsity in the coefficient estimates and thus, in the resulting network matrix. As λ increases, the LASSO penalty starts to force some coefficients to become exactly zero, effectively performing variable selection. This means that LASSO can identify and exclude irrelevant covariates from the regressions composing the model. 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 was extensively validated in dedicated studies (Epskamp & Fried, 2018; Foygel & Drton, 2010; Haslbeck & Waldorp, 2020). This procedure allows to compute *node predictability*, which is the portion of its variance that is explained by the connections it has with other variables. Since all variables are modeled as continuous, R2 values are reported. Moreover, modeling the selected variables as continuous allows for the interpretation of edges as partial correlation coefficients (Burger et al., 2022).

After the mgm network estimation, H1 and H2 are tested. The small-worldness of the network is assessed through the statistical test proposed by Humphries and Gurney (2008), which compares the clustering coefficient and the connectivity of the target network with those of a simulated random network of the same size. The clustering coefficient of a network measures the extent to which its nodes form cliques, which are fully connected graphs (Watts & Strogatz, 1998). Connectivity is measured by the average shortest path length, calculated on the absolute weighted adjacency matrix. It is equal to the mean value of all minimum path lengths connecting each pair of network nodes. 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. Formally, a network is said to be a small-world network if the test produces a value greater than 1. The centrality of network nodes is calculated with the strength metric. The strength score of a given node is obtained by summing all absolute values of the edge weight of the relationships in which it is involved. Although many metrics could have been computed, research suggests avoiding the application of other conventional centrality conceptualizations to Graphical Models of this kind. Indeed, the calculation of measures such as betweenness or closeness relies on assumptions that are often violated in a network where nodes do not have agency (Bringmann et al., 2019).

### Moderated ggm

The third research hypothesis 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 into low and high levels of self-reported anger, estimate two network models, and compare them with a 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). Both 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 relationship between a pair of variables is supposed to be constant within a group, and different between them. One way to resolve both obstacles is the adoption of a Moderated Network Model (MNM) (Haslbeck et al., 2021). This model estimates edge parameters 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 models a moderation effect of a selected continuous variable. Thus, MNM outputs two sets of parameters, one corresponding to each pairwise interaction between network nodes, and one to each retrieved three-way interaction between node pairs and the moderator 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.

### Ising

To test H4, this article implements a network simulation, which requires a data reduction process where variables are dichotomized[[1]](#footnote-1). Network estimation of this data type follows the same procedure detailed in the above paragraphs, fitting a mgm where nodes are modeled as binary variables. However, linear regressions are replaced by logistic ones. 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 estimates two additional classes of parameters that are discussed in Section 3.3.

### bootstrap

Network analysis of multivariate data results in a parameter matrix. However, these values are only point estimates of the conditional associations of a dataset. To evaluate their robustness, it is necessary to perform bootstrapping techniques (Epskamp et al., 2018). Non-parametric bootstrap allows building bootstrapped confidence intervals around edge parameters. For each estimated network, 10000 samples are built by sampling individuals with replacement from the original one. Edges parameters are re-estimated in each sample, and their aggregation leads to bootstrapped confidence intervals, encapsulating the central 95% of the bootstrapped distribution. Results of this procedure are made available in Figures 2 and 4 of the Supplement. The same procedure is applied to check the robustness of the moderation effects of anger (Table 2 of the Supplement).

To inspect the stability of strength centrality metrics case-dropping bootstrap is implemented. Observations are gradually dropped from the sample and at each step centrality scores are calculated. 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, to directly compare two given edges or strength scores, bootstrapped difference tests are computed. Non-overlapping bootstrapped CIs are evidence of significant differences between point estimates (ibid.).

## 3.3 Network simulation

### More on the model

Given the paucity of temporal data on attitudes toward inequality, H4 is tested through a simulation of network dynamics. Following the CAN model (Dalege et al., 2016), the temporal development of the network of attitudes towards inequality is supposed to conform to the Ising model (Ising, 1925). Nodes can assume two states (-1; +1). Originally, these states represented 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:

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Description automatically generated

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. Therefore, network configurations in which nodes characterized by positive [negative] thresholds are tied by positive [negative] edges reduce the level of energy expenditure. The Hamiltonian function encodes the central axiom of CAN by modeling the fact that attitude networks strive for low energy expenditure configurations, according to the need for cognitive consistency.

### Simulation

The simulation mocks a series of successful persuasion attempts targeting one network node at a time, and has been already applied to diverse socio-political attitudes (Dalege et al., 2017; Schlicht-Schmälzle et al., 2018). Manipulations are operationalized as an increase of nodes’ thresholds (𝛕). The dependent variable of this simulation is the sum score of all evaluative reactions[[2]](#footnote-2), measured before and after each manipulation. H4 is confirmed if changes in central -rather than peripheral- nodes produce downstream effects. A downstream effect occurs when the state change of a given node reverberates into a state change of at least one other.

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). 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

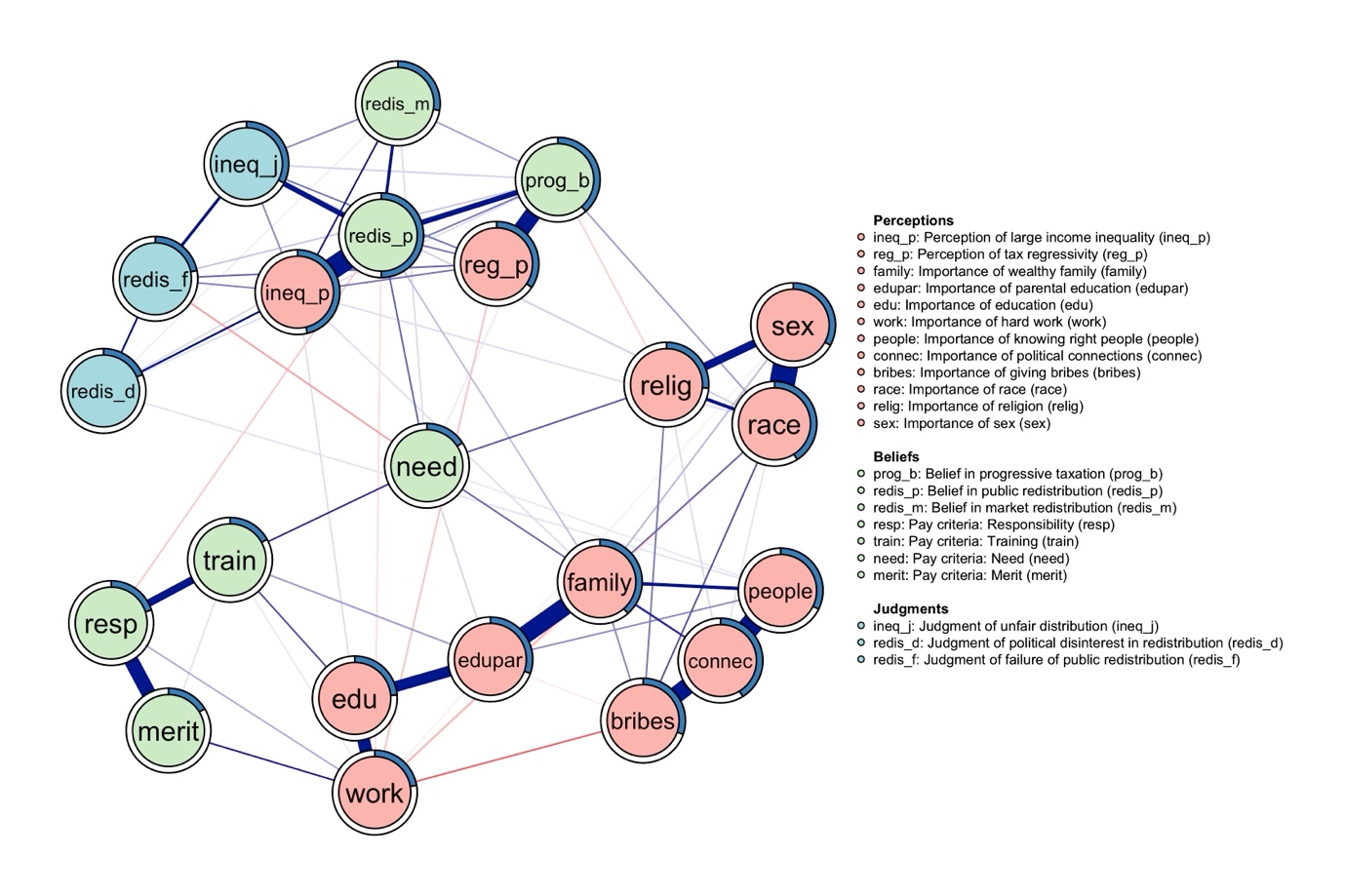
## 4.1 Modelling attitudes toward inequality as a network

### Brief description of the levels of these attitudes

Table 2 reports the descriptives of the ten variables after their dummy recode. Most respondents judge Italian society as highly unfair (*j\_ineq*), perceive differences in income as too large (*p\_inc\_ineq*), consider politicians to be uninterested in applying redistributive policies (*j\_red\_unca*), and believe in the importance of public redistribution (*b\_red\_pub*), and progressive taxation (*b\_tax*). On average, the members of the sample also endorse critical judgments about existing redistributive policies (*j\_red\_fail*), they perceive that the distribution of resources is unequal (*p\_ineq*), think companies should reduce the pay gap between their employees (*b\_red\_mar*), and prefer equalitarian societal assets (*b\_ineq*). Finally, the item *p\_tax* has the lowest mean, indicating that high perception of inequality, egalitarian beliefs, and critical judgments about distribution are not mirrored by the perception that taxation is too regressive.

### Description of GGM

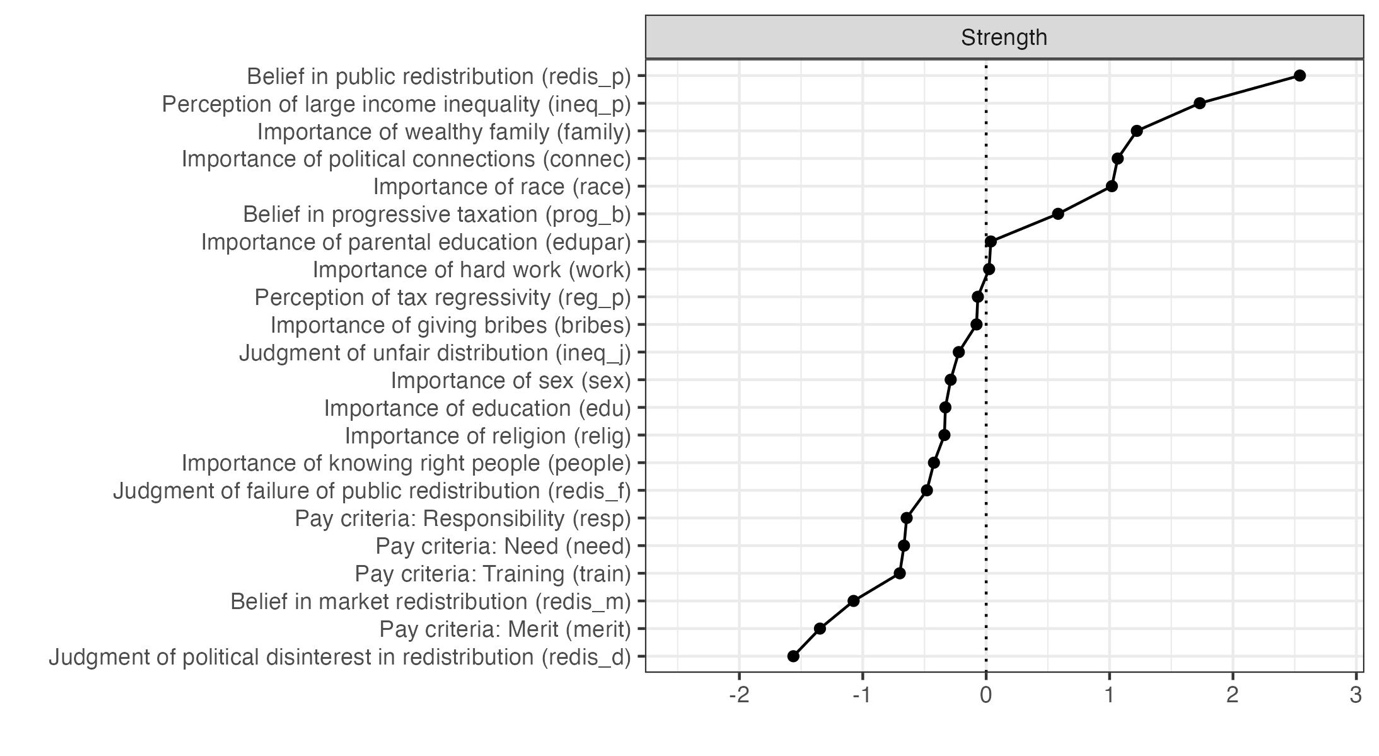
Figure 1: The network of attitudes towards inequality



*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 was 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.

### Description of centrality and small world index

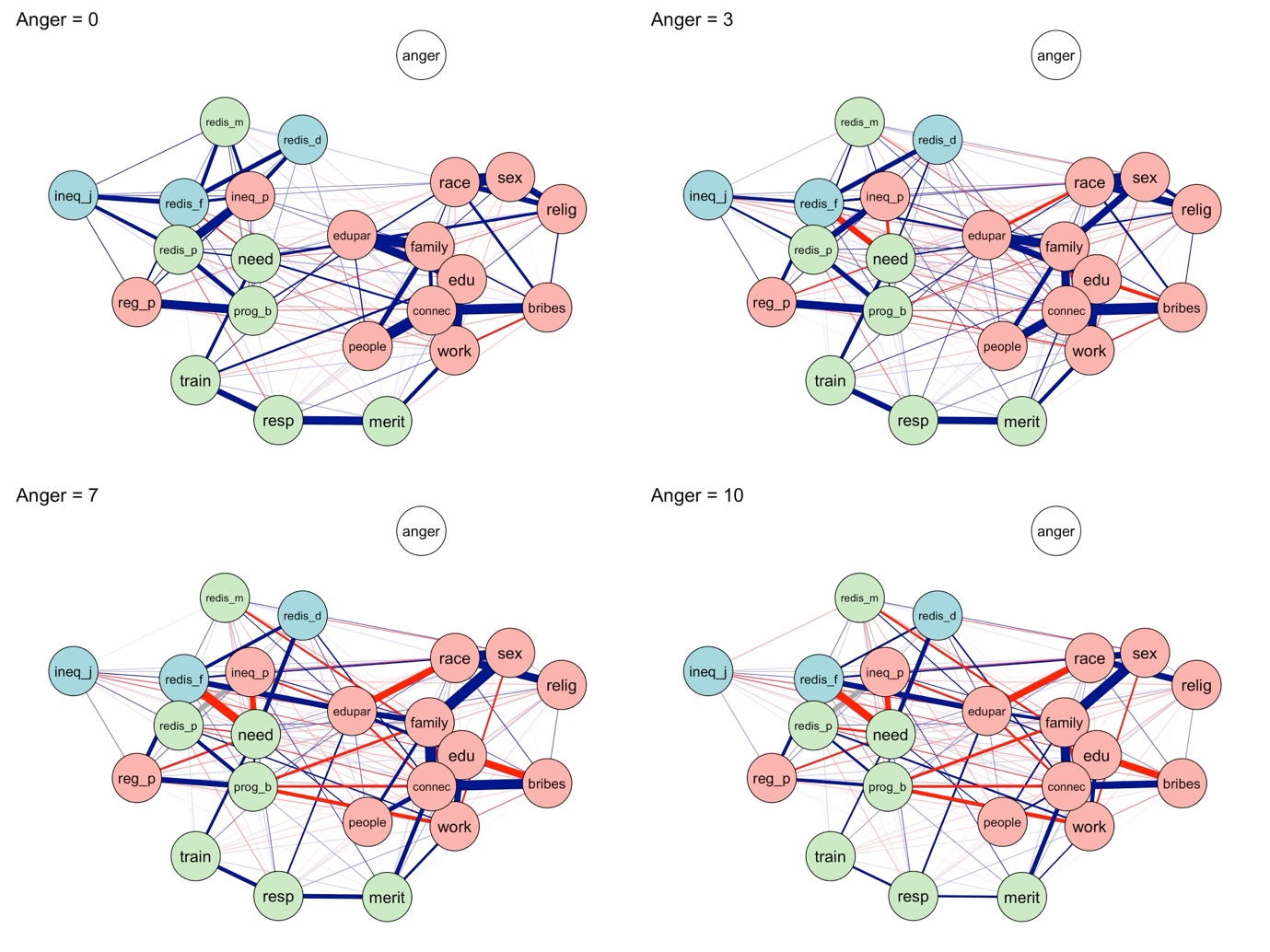
Figure 2: Node centrality



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

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

Figure 3: Moderated Gaussian Graphical Model of the 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.

## 4.3 Simulating change in the network of attitudes towards inequality

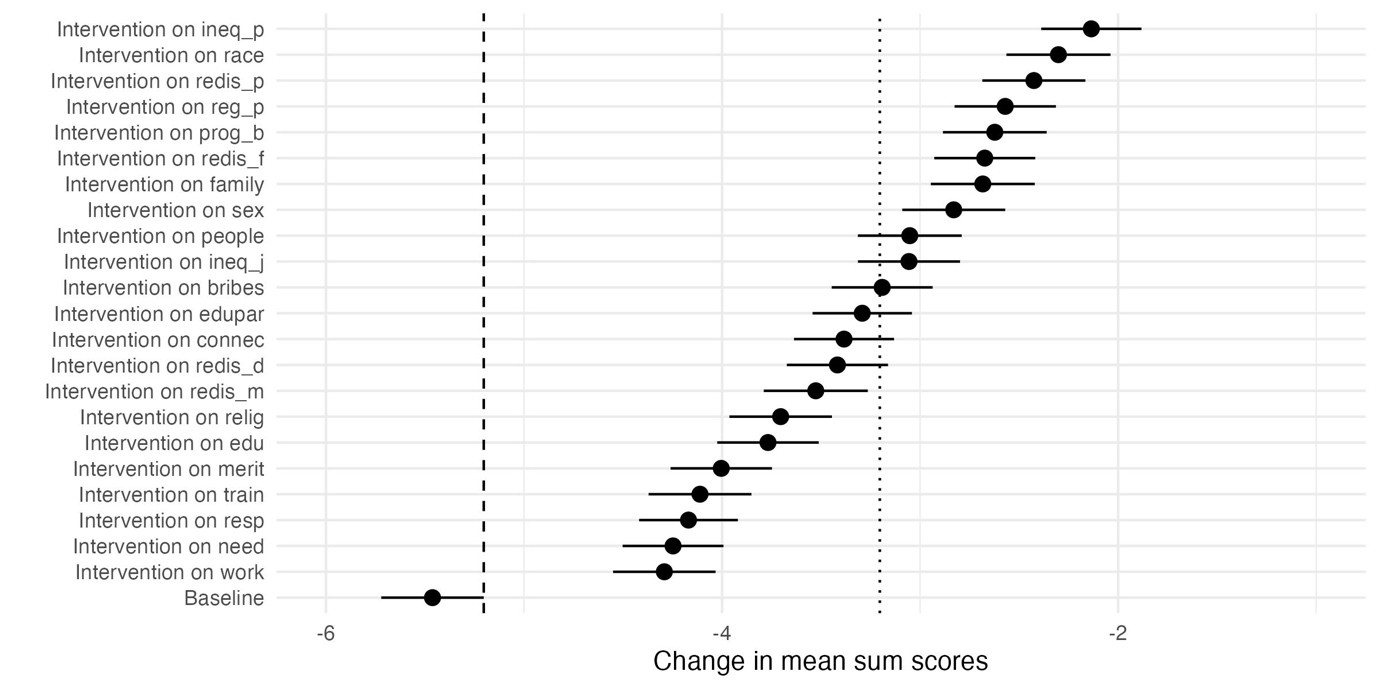
Figure 4: Ising network and centrality table

A diagram of a network

Description automatically generated

*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 targetting 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.

## 5. Discussion

## 6. Conclusions

## 7. References

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1. Variables were truncated considering their mean values. Descriptives are made available in Table 2 of the Supplement. Additional analyses confirmed dichotomization of all nodes following different criterias (truncation at two, or at three out of five points) does not impact on the estimated network. [↑](#footnote-ref-1)
2. 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-2)