Modeling, estimating, and simulating:

formalizing attitudes towards inequality as a complex network

Arturo Bertero[[1]](#footnote-0)

Gonzalo Franetovic[[2]](#footnote-1)

# Abstract

Our work represents the first attempt to model attitudes towards inequality as a network of interacting evaluative reactions. This multidimensional concept is measured through people’s perceptions, beliefs, and judgments about inequality, redistribution and taxation. We apply the Causal Attitude Network Model to ISSP 2019 data representative of the Italian population. This model renders survey variables as nodes of a network whose edges represent their estimated partial correlations. The network reveals the between-person structure of people’s understanding of inequality. Findings show that these evaluative reactions form a fully connected network organized into two communities. Within these substructures, variables interact regardless of their nature -perceptions, beliefs, and judgments- or their topic -inequality, redistribution, and taxation. Perception of large income inequality and belief in public redistribution are the most important components of the network of attitudes towards inequality in Italy. Consequently, when targeted with simulated manipulation attempts, these nodes produce broad changes in the attitude network, affecting neighboring ones. Our results have important implications for the literature on distributive justice and attitude networks, as they offer a multidimensional comprehension of these attitudes and provide evidence on their dynamics.

# Introduction

Inequality represents one of the greatest challenges in contemporary societies. The rise of disparities between social groups has reached unprecedented levels over the last decades [(Atkinson et al., 2011; Keeley, 2015; Lansing & Markiewicz, 2018)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=806128409900638&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:4dec1e2f-b58b-4966-88d4-ef58733e8a40,0a3c846c-7570-4913-bd72-3afd46468081:913c485d-603a-4952-a126-b6b80b14c892,0a3c846c-7570-4913-bd72-3afd46468081:0a0f849f-f216-4390-b847-41da246e2b2e), establishing wide differences in the conditions under which people develop their lives [(Wilkinson & Pickett, 2009)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=8035794181930467&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:07323f85-b5ff-4eb7-bcae-e369049beafe). However, the widening of social gaps has not led to a corresponding increase in people's concern about inequality [(A. Alesina & Glaeser, 2004; Kenworthy & McCall, 2007; Lierse et al., 2022; Lübker, 2007)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=4104090827453627&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:da5a5ae7-0cfb-41f6-86a9-e68b605c1aee,0a3c846c-7570-4913-bd72-3afd46468081:f719d8fd-f939-4ad1-a467-2bc25c702c01,0a3c846c-7570-4913-bd72-3afd46468081:5f7b7aef-ee15-41af-a3d6-a044595410c2,0a3c846c-7570-4913-bd72-3afd46468081:651b6821-94bf-4ac7-9220-0b284469a1a8), highlighting that individuals tend to misunderstand the size of inequality, usually underestimating [(Hauser & Norton, 2017; Norton & Ariely, 2011)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=4834694202346116&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:c10b6e8a-d932-4834-ae32-960780fb65f9,0a3c846c-7570-4913-bd72-3afd46468081:8a8f7b3a-53d8-45bc-a59b-76051778caec) but sometimes overestimating it [(Chambers et al., 2014)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=7349370109661253&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:fd703ac6-669d-45f9-b11c-3abcfd3d0a4a). Therefore, the distribution of resources across societies does not have a direct link on how people understand inequality [(Trump, 2023)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=07609306003643035&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:548f8074-084b-410b-816d-44ea49789c66). 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)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=4107276106993858&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:8407923d-0c1c-41f9-84f8-263ed4a8b3ac), political science [(Larsen, 2016)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=45085961696060795&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:760e42d7-ab08-46a2-9565-732d8a898100), economics [(Luttig, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=3455536365070203&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:4bce9add-eff0-4cce-b6a1-97e002a199dd) and social psychology [(Hegtvedt & Isom, 2014)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=14679726987831432&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:26d431d9-3e39-404e-8853-08b2254fdc49).

However, research on distributive justice has not systematically addressed attitudes toward inequality [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=046229852733590704&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a). In fact, perceptions, beliefs, and judgments about resource distribution are usually studied in isolation, neglecting one of these dimensions or other related topics, such as attitudes toward redistribution and taxation. To overcome this limitation, we adopt a network perspective on attitudes towards inequality, applying the Causal Attitude Network [CAN] model [(Dalege et al., 2016, 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9332588039071795&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:12564573-44ed-454b-a58b-80c7e2932eec,c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). In this theoretical framework, attitudes towards inequality are conceived as a network of interacting evaluative reactions. These components become nodes of a network whose connections are estimated from survey data. CAN allows us to avoid the aggregation of variables into indices, as is commonly done when latent variable measurement models are adopted. This ensures a holistic comprehension of how people understand inequality, by recovering the between-person structure of a varied set of perceptions, beliefs, and judgments. Moreover, attitudes towards inequality are still underinvestigated in the Italian context, despite some relevant contributions [(Carriero, 2016; Carriero & Filandri, 2021)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=8137767987655191&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:ad69dfd0-84d5-46c9-9a1f-3a335aecf1e0,0a3c846c-7570-4913-bd72-3afd46468081:6472c929-820b-40c9-9d3e-8c8e91febc32). This motivates the choice of this country as a research setting.

Therefore, the present work has three objectives. First, we *model* attitudes towards inequality as a network of interconnected conceptions regarding inequality, redistribution, and taxation. Second, we *estimate* this network from survey data representative of the Italian population. Third, we investigate attitude change by *simulating* persuasion attempts on important and marginal nodes, to demonstrate that interventions on the former have larger effects than those on the latter. The paper is structured as follows. We begin by discussing distributive justice theory to find out the main components of these attitudes, and how they relate to each other. Then, we explain why latent variable models are not suitable to answer our threefold aim, and we propose to surmount their shortcomings through the adoption of the CAN model. Next, we describe the data, variables, and method used. Afterward, we present our results regarding network estimation and simulation of attitudinal changes. In the discussion, we engage with the literature on social justice and attitude networks to situate our results in a broader context. Finally, the conclusions highlight the main contributions of this research and its limitation, while suggesting avenues for future research.

# Theory

## Attitudes towards inequality

Attitudes are “general evaluations that people hold regarding a particular entity, such as an object, an issue, or a person” (Eaton & Visser 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 political science, attitudes are studied because they strongly predict relevant social and political behaviors [(Hatemi & McDermott, 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=3636508571893081&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:70055693-8e0c-48d5-a235-d6cf829109bd). 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 (Maitland, 2008). Typically, Multi-Item Likert scales are employed, so that an individual’s attitude towards the object is represented by the sum of the responses to each statement, or by some weighted combination of these scores (ibid.).

Particularly, attitudes towards inequality represent a multidimensional concept, including perceptions, beliefs, and judgments about the distribution of resources within a society [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=5757706566545323&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a). Perceptions refer to subjective estimations about how much inequality exists. Their measurements are varied and range from general indicators of individual agreement with the statement that "income differences are too large", to the association between images of distribution pyramids simulating resource allocation, or the perceived wage gap between occupations at the extremes of the labor hierarchy [(Castillo et al., 2022; Heiserman & Simpson, 2021)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=8684153703911824&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:9bd8c586-f281-4955-8f3c-6e51987088c3,0a3c846c-7570-4913-bd72-3afd46468081:a123e7af-25ea-45ba-a323-df8658e82f3f). Instead, beliefs correspond to normative ideas about how much inequality people think ought to be. This dimension is frequently measured with indicators similar to the ones of perceptions, but situating individuals in an ideal scenario [(Osberg & Smeeding, 2006)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=8680895255776894&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:82038a60-7e56-4476-bf1f-5e139deb9d12). Finally, judgments represent evaluations of existing levels of inequality and refer to how good, desirable, fair, or just individuals rate the current distribution [(Kelley & Evans, 1993)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=09918777798069278&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:84066d2c-6a8d-4b9a-b094-572868f70c2d).

Since inequalities result from many social, economic, and political arrangements [(McCall & Percheski, 2010)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=5348573626712421&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:c4eec204-74a1-4c78-bf3a-40afe171a67a), social research establishes several other fields that are highly interconnected and important for comprehending peoples’ attitudes toward inequality [(McCarty & Pontusson, 2011)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=30466983664219505&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:bd7459eb-9659-4426-86b7-53497e728b82). 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)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=9714506199156214&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:deb7faec-9fc1-4743-8933-7f80dcb2fafa,0a3c846c-7570-4913-bd72-3afd46468081:a96ae13c-431a-4121-8355-4b836f6bf16d,0a3c846c-7570-4913-bd72-3afd46468081:a8515a57-2c54-4307-9024-b949519750c6). Moreover, how people comprehend taxes and redistribution are topics that the literature relates to perceptions, beliefs, and judgments about inequality [(Bartels, 2017; Berens & Gelepithis, 2019; Bussolo et al., 2021; Choi, 2021; Fatke, 2018; García‐Sánchez et al., 2020; Iacono & Ranaldi, 2021; Redmond et al., 2002; Trump, 2023)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=682292873682979&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:ae1ff779-9441-4130-a7b1-4dabdaa2ba97,0a3c846c-7570-4913-bd72-3afd46468081:548f8074-084b-410b-816d-44ea49789c66,0a3c846c-7570-4913-bd72-3afd46468081:e1beb8e5-0fbb-4ea2-a5d6-179be00ba4df,0a3c846c-7570-4913-bd72-3afd46468081:421437b9-406d-4b60-b96d-48904371aa9e,0a3c846c-7570-4913-bd72-3afd46468081:9aab537e-96b0-4c30-9d67-7516a018194f,0a3c846c-7570-4913-bd72-3afd46468081:fe309770-9b05-4e81-a252-a4899471bd60,0a3c846c-7570-4913-bd72-3afd46468081:b1252f7e-ebcf-43ff-872b-b177c530b2f4,0a3c846c-7570-4913-bd72-3afd46468081:09017208-6af6-4ca8-939a-823b3e612f39,0a3c846c-7570-4913-bd72-3afd46468081:2d93587f-9510-4e10-b201-fde8c4b1b3a7). Therefore, to explore how people understand inequality it is essential to dig also in the subjective comprehension of both of the above-mentioned topics.

The literature has found various relationships between how people perceive, believe, and judge inequality, taxes, and redistribution. One of the most researched associations is 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 is known as the anchoring effect and describes how people adjust their expectations according to their perceptions in surveys [(Pedersen & Mutz, 2019)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=23981016420764867&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:0ab7e1b2-75f4-4266-875c-3f8d4dc8d157). Another commonly found association is that between the perception of inequality and the belief in public redistribution [(Gimpelson & Treisman, 2018; Kuhn, 2011; Kuziemko et al., 2015; Trump, 2023)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=3636137194688085&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:3933589e-f6a2-4cbd-bb20-9de2519cf104,0a3c846c-7570-4913-bd72-3afd46468081:e139e873-ed74-4984-9c94-e020458801d6,0a3c846c-7570-4913-bd72-3afd46468081:548f8074-084b-410b-816d-44ea49789c66,0a3c846c-7570-4913-bd72-3afd46468081:a1517b87-03d2-4c62-b8b2-b725b37bd76f), a relation particularly significant among people that perceive to be at the top of the social ladder [(Fatke, 2018)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=06322328901150243&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:9aab537e-96b0-4c30-9d67-7516a018194f) and who reject beliefs that justify inequality [(García‐Sánchez et al., 2020)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=32818322392118726&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:2d93587f-9510-4e10-b201-fde8c4b1b3a7). Indeed, people's subjective social positions [(Brown-Iannuzzi et al., 2015)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=13751406938037647&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:45821baf-6f5d-4433-9485-a4fbaa9d9c74) and their explanations of inequality [(Christina, 2001)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=4505203791293879&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:dec53053-6071-4b11-9ff6-61886bdeb61d) 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 the way in which people perceive inequality [(García‐Sánchez et al., 2020)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=7928023009146615&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:2d93587f-9510-4e10-b201-fde8c4b1b3a7)**.**

Besides cross-sectional investigations, scholars also engaged in the study of how individuals' attitudes towards inequality change, by modeling the impact that one element can have on the properties of the others, without consistent results. Indeed, Cruces et. al. [(2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=0040406763269904555&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a6d66e35-d47f-4dd3-acf3-1b1a09a7b5e3&options=%7B%22items%22%3A%7B%220a3c846c-7570-4913-bd72-3afd46468081%3Aa6d66e35-d47f-4dd3-acf3-1b1a09a7b5e3%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D) highlighted the importance of perceptions about distributional beliefs. Using an experimental survey design, applied in Argentina, they observed how people shape their perceptions of inequality and how they affect their preferences for redistribution. Individuals who overestimated their relative position tended to be more supportive of redistribution when informed of their true placement in the social hierarchy. The experimental research of Campos-Vazquez et al. [(Campos-Vazquez et al., 2022)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=1738906559742167&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:f64d378a-2cc8-477f-bdb3-4db0890c3e60), 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’ perception of inequality did not provoke changes in their normative beliefs about income distribution, social mobility, and tax rates

Although being a multidimensional concept, attitudes towards inequality are usually studied unsystematically. Indeed, [Janmaat (2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=43354673346478734&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a&options=%7B%22manual_text_override%22%3A%22Janmaat%20(2013)%22%7D) elaborated a systematic review of this topic and showed that there is almost no research that links the three attitudinal dimensions -perceptions, beliefs, and judgments. An important exception is the study by Redmond et al. (2002), which compares the attitudes of the inhabitants of Eastern and Western countries, finding that the judgments about income redistribution of the former are more critical than those of the latter. The authors explain this result with the greater difference between perceptions and beliefs about inequality within the East. However, this hypothesis was not statistically tested, calling into question the effectiveness of this assertion [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=857119927364702&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a). More recently, García‐Sánchez and colleagues [(2020)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=6043220272474308&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:2d93587f-9510-4e10-b201-fde8c4b1b3a7&options=%7B%22items%22%3A%7B%220a3c846c-7570-4913-bd72-3afd46468081%3A2d93587f-9510-4e10-b201-fde8c4b1b3a7%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D) showed that perceptions and beliefs about inequality are not directly related to individuals’ support for public redistribution. Indeed, they found that perceived inequality is positively correlated with a greater willingness to redistribute public resources, but only for those who reject beliefs that justify inequality based on merit and equality of opportunity. In contrast, people who support these beliefs do not show this positive correlation, and the same moderation effect was found for the relationship between perceived economic inequality and support for progressive taxation. Therefore, despite these few attempts, the literature lacks a study investigating the internal structure of attitudes toward inequality. To the best of our knowledge, this article represents the first such contribution.

## Shortcomings of latent variable models

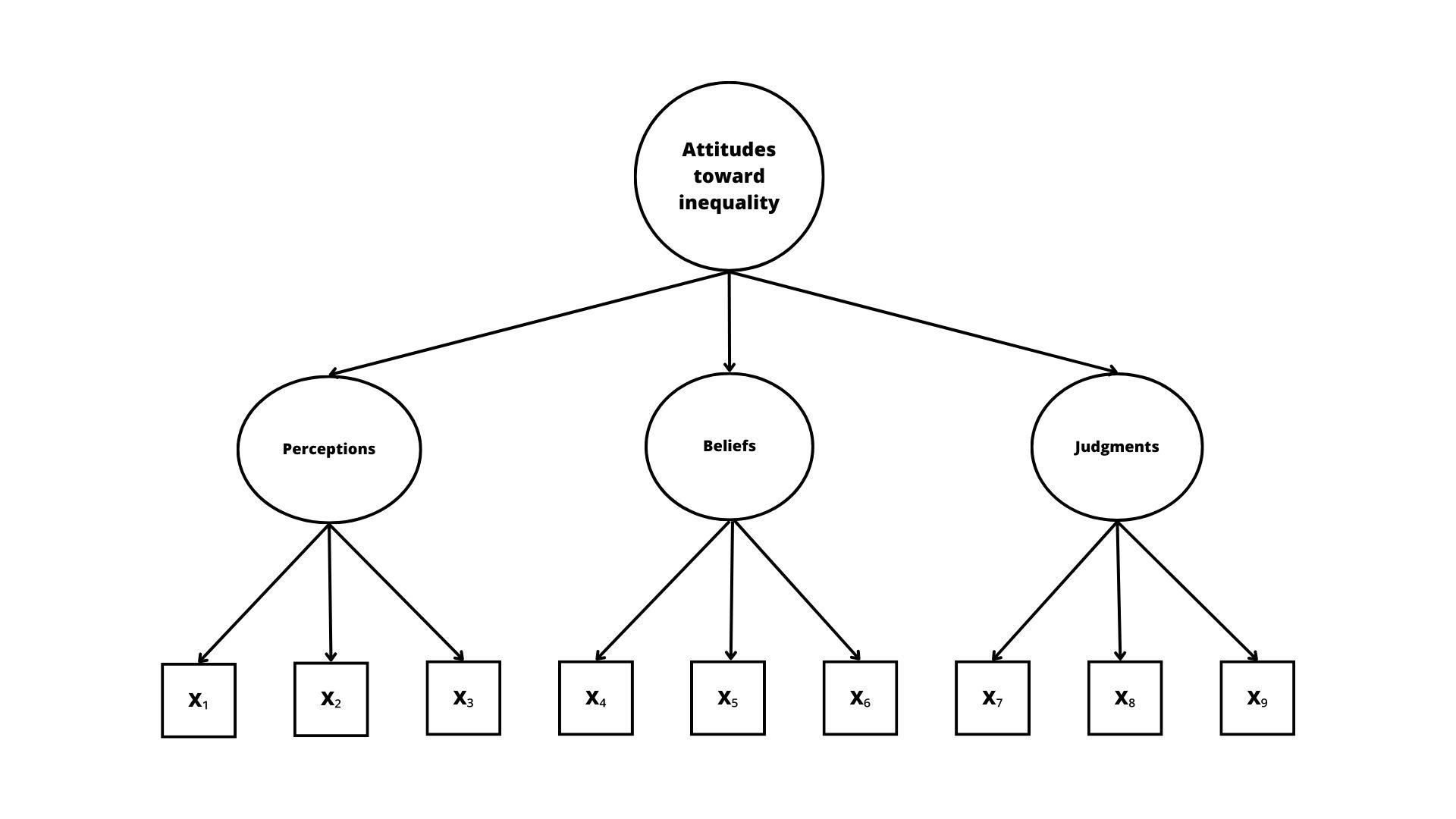
To fill the gap in the literature identified in the previous section, it is necessary to investigate the relationship between a wide set of variables. To do so, we resort to a measurement model without latent variables. This is an innovation since most research on the topic conforms to this approach [(Heiserman & Simpson, 2021; Kluegel & Smith, 1986; Kreidl, 1998, 2000)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=8559608995715572&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:5cc6cd8e-9784-4936-b989-e74ab81455d3,0a3c846c-7570-4913-bd72-3afd46468081:a123e7af-25ea-45ba-a323-df8658e82f3f,0a3c846c-7570-4913-bd72-3afd46468081:09a629ae-8498-4406-9b7b-93b36b871780,0a3c846c-7570-4913-bd72-3afd46468081:150c407e-3748-4053-8372-4ab9e02d334f). Figure 1 below exemplifies its application to attitudes towards inequality. This construct is decomposed into three dimensions -perceptions, beliefs, and judgments [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=11214942330477096&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a) - that are assessed through survey items. The attitude functions as a latent variable causing specific responses to each question. As a consequence, items insisting on the same dimension can be aggregated into three indexes. A serious shortcoming of these models is their unrealistic explanation of the *positive manifold.* This concept was developed in cognitive psychology to describe positive correlations between individual scores on different intelligence tests. Notoriously, Spearman (1961) proposed that these correlations are spurious since caused by the latent factor “general intelligence”; once its role is taken into account, correlations are all explained away. More recently, social psychology scholars have used this concept to describe associations between different items referring to the same attitude [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=5454173361201949&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). Indeed, the scores of variables tapping affective, behavioral, and cognitive components of an attitude are usually positively correlated[[3]](#footnote-2) (Bagozzi & Burnkrant 1979; Bagozzi & Burnkrant 1985; Breckler 1984; Haddock et al. 1993). Therefore, in Figure 1 the manifold would be produced by a set of positive correlations between scores of the observed variables X₁ - X₉.

A latent variable explanation of between-items correlations rests on two assumptions that are problematic in the attitude domain [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=906380895666373&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). First, latent measurement models assume that items are *locally independent* (Bollen, 1989). This means that once the influence of the latent variable is controlled for, the scores of one item should not be influenced by those of any other. In Figure 1, this means that an individual response to an item tapping perception of inequality should be locally independent of the score of an item measuring judgments about existing inequality. However, this assumption clashes with cognitive consistency theories [(Dalege et al., 2016, 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=039586812071600086&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:12564573-44ed-454b-a58b-80c7e2932eec,c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). In particular, consistency is central to both balance and cognitive dissonance theories. In Heider’s balance theory of attitudes, people strive for consistent attitudes to reduce psychological discomfort (Heider, 1946). Therefore, social relationships are based on consistent attitudes, which means that if an individual has a positive attitude toward another person, they are likely to interact. Hence, this theory predicts that in the presence of an unaligned set of attitudes, an individual is likely to modify either his/her relationships or his/her attitudes. Cognitive consistency is also the focus of cognitive dissonance theory (Festinger, 1962). As the former theory, this approach posits that individuals are motivated to reduce or eliminate friction between their attitudes, to avoid psychological distress. Cognitive dissonance theory extends Heider’s one, in that it specifies that individuals are motivated to reduce cognitive inconsistency not only in their attitudes but also while gathering new information about the attitude object. Both theories collude with the local independence hypothesis by predicting that individuals actively seek an aligned state of their attitudes, thus postulating an implicit influence between observed items. In Figure 1, this translates into the prediction that when filling out the survey, respondents are likely to express coherent answers to items X₁ - X₉, rather than addressing them in isolation.

In addition, latent variable models assume that items measuring the same dimension are *exchangeable*, meaning that their correlations should be constant (Bollen, 1989). Therefore, additional items insisting on that dimension only serve to enhance the reliability of the survey, rather than adding independent information [(Bollen & Lennox, 1991; Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=03321504161460387&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699,c61b91da-fa6e-4348-80b6-c2428280b16a:b9ffb75e-b9e0-4af2-9aa3-8ccd08307df0). This assumption is undemanding for physics, where if the temperature of a room is measured through a thermometer, adding a second one and averaging their estimates would increase the reliability of the measurement, but not its validity (Borsboom, 2005). However, in the field of attitudes this assumption implies that if an observed variable fully captures the latent variable which is intended to measure, other valid indicators of the same latent variable would be deterministically associated with it. Hence, a change in one observed variable should be matched by a change of the same magnitude on all others [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=533682538306498&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). This assumption is hardly defendable in the attitude domain, where the literature showed the high internal inconsistency of belief systems. This phenomenon was first addressed by Converse [(2006)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=6094912643668796&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:fa194e42-3c3a-4449-a49d-41f18dbce688&options=%7B%22items%22%3A%7B%22c61b91da-fa6e-4348-80b6-c2428280b16a%3Afa194e42-3c3a-4449-a49d-41f18dbce688%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D), who highlighted the lack of coherence and durability of political attitudes in North American public opinion. More recently, attitude inconsistency was formally defined as a situation in which the components of an attitude are in conflict, or in which they clash with their overall evaluation of the attitude object (Maio et al., 2020). In the field of inequality, inconsistency was revealed already in the precursor work of Kluegel and Smith [(1986)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=9086521424858082&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:5cc6cd8e-9784-4936-b989-e74ab81455d3&options=%7B%22items%22%3A%7B%220a3c846c-7570-4913-bd72-3afd46468081%3A5cc6cd8e-9784-4936-b989-e74ab81455d3%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D). This contribution emphasized that North Americans tend to explain inequality through both individualistic and structuralistic attitude elements. Therefore, explanations of inequality pointing to individual agency and those based on structural determinants are not mutually exclusive [(McCall, 2013; Mijs, 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9630063992093179&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:5f0c31fa-666f-4d55-b3d8-60222c024397,8841a519-4b57-4192-9afd-0d3b615bff40:35e1b457-26ce-4a3b-9a62-2a469b22c996). Moreover, researchers showed that perceptions and beliefs about inequality are not linearly related to the levels of support towards public redistribution (García‐Sánchez et al., 2020). Therefore, contrary to the prediction of the exchangeability assumption, we do not expect items X₁ - X₉ in Figure 1 to be fully aligned (i.e.: perfectly correlated).

In sum, this concise description of the measurement model underlying attitude research has shown that latent variable explanations of their positive manifold are based on two unrealistic assumptions. First, items measuring the same concept are unlikely to be fully independent, since human cognition is at least partially driven by the need for consistency. Second, these items are hardly ever completely exchangeable, as demonstrated by the inner structure of social and political attitudes, which is often inconsistent. Therefore, latent variable models fail to combine this evidence without violating their assumptions.

*Figure 1: Latent variable model of attitudes towards inequality*

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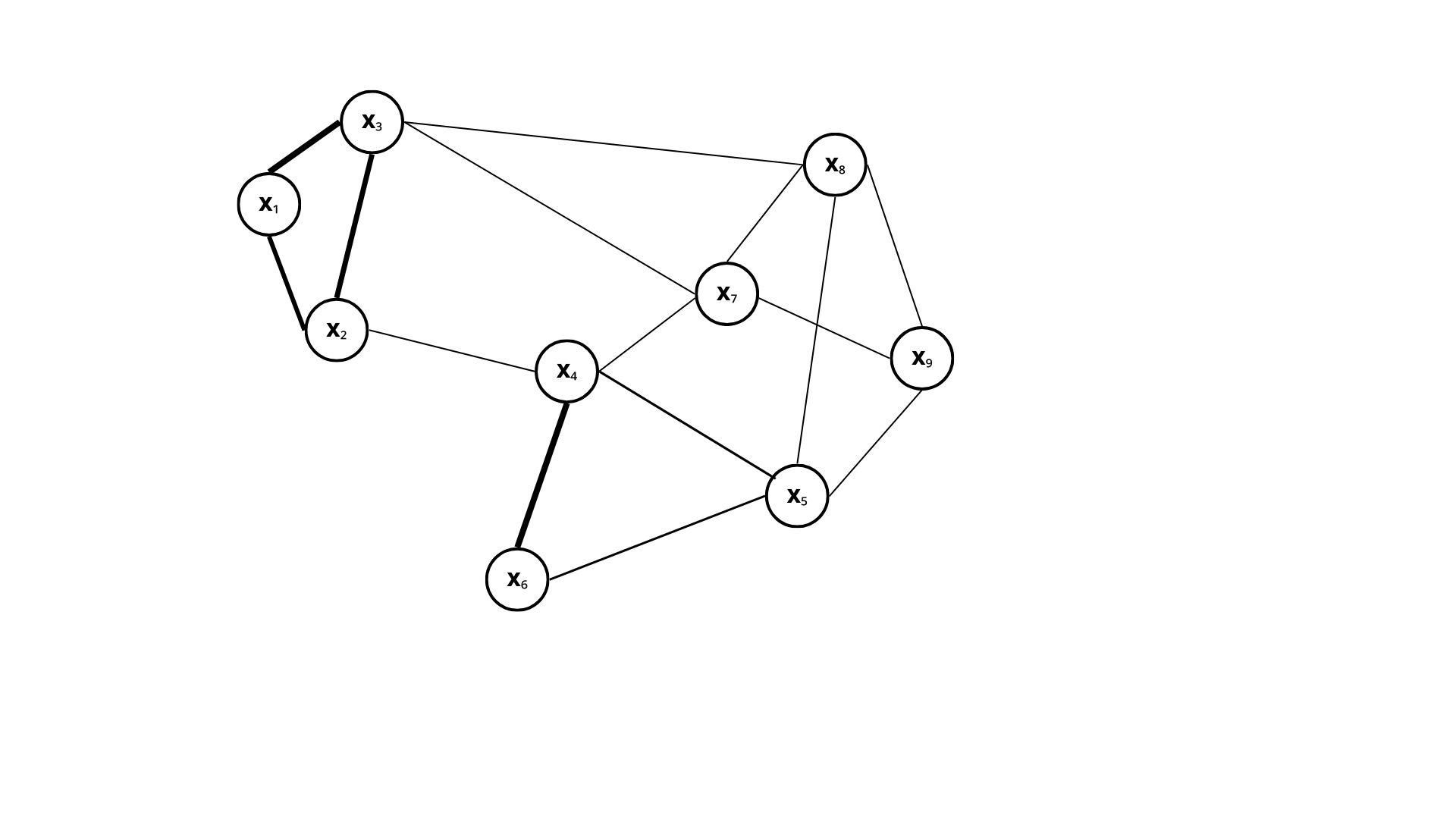
*Note:* Latent variable model for the attitudes towards inequality construct. This concept is assumed to be an unobservable variable featuring three dimensions, each measured by multiple survey items. These items display the positive manifold, but their correlations are spurious, being caused by the latent variable.

## Modeling attitudes as networks: the CAN model

The CAN model has recently been proposed to address the contradictions emerging from latent variable explanations of positive manifold [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=22371198610713006&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). The core idea of this account is that between-items correlations are not spurious but rather endowed with bidirectional causal power. In latent variable models, causality flows from an unobservable and abstract variable to a set of observed survey items, whose correlations are considered spurious (as in Figure 1). CAN models an attitude as a network of evaluative reactions engaging in reciprocal and causal interactions. The reason why correlations are meaningful - rather than spurious - is that evaluative reactions exercise direct influence on each other. As explained earlier, this is a consequence of the need for consistency, which requires the alignment of evaluative reactions to reduce psychological distress (Festinger, 1962; Heider, 1946). Figure 2 shows a simplified application of the CAN model to attitudes towards inequality. This concept is measured through the same set of variables as in Figure 1 (X₁ - X₉). Figure 2 shows that attitude networks are composed of two classes of entities. Survey variables are represented by network nodes. These are linked by undirected edges, which are indicative of partial correlations estimated from the data. Hence, edges vary in strength, and this is reflected in their width. This implies that in the CAN model, an item that measures perceptions of inequality (e.g., X₁) should causally interact with others that measure beliefs and judgments about inequality. For example, a high perception of inequality can lead to egalitarian beliefs and also unfair judgments about the existing income distribution. Furthermore, the main assumption of the CAN model is that these relationships are reciprocal, as produced by the cognitive consistency pressures that drive each item to interact.

If the need for consistency were the sole driver of human cognition, attitude networks would always show total alignment (e.g.: a situation in which items X₁ - X₉ are all positively correlated, meaning that high [low] perceptions of inequality are perfectly mirrored by egalitarian [inegalitarian] beliefs and judgments of unfairness [fairness] about inequality. However, attitudes in general [(Converse, 2006)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=8979493996124588&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:fa194e42-3c3a-4449-a49d-41f18dbce688), and those about inequality in particular (García-Sánchez et al., 2020), rarely show perfect internal consistency. This provided the base for a critique of the items' exchangeability assumption. Moreover, individuals are also motivated to build *accurate* attitudes (Chaiken, Liberman, & Eagly, 1989), and it has been observed that a trade-off between the need for consistency and the need for accuracy permeates decision-making processes (Payne et al., 1993). Accurate attitudes would lead to a situation where many evaluative reactions do not align, meaning that an individual is capable to assess her or his position on each survey item without considering the related ones. As a consequence, individual attitudes are infrastructured by the tension between two opposite tendencies: the need to correctly depict the attitude object, and the one to minimize psychological discomfort, optimizing cognitive consistency [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=6371307040161741&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). This friction is incorporated into the CAN model through the concept of network clusters. Clusters, or communities, are subsets of network nodes that are more likely to interact with each other than with other nodes. When nodes of an attitude network cluster together, the whole system can balance the opposite tendencies: aligned nodes can gather - allowing for internal consistency - while misaligned ones can coexist - being compartmentalized in different communities. This is visible when contrasting Figure 1 with Figure 2, where items tapping perceptions (X₁ - X₃), beliefs (X₄ - X₆), and judgments (X₇ - X₉) form three separate clusters, meaning that variables belonging to each dimension of attitudes towards inequality have a high tendency to align to each other.

Figure 2: Application of the CAN model to attitudes towards inequality



*Note:* Application of the CAN model to attitudes towards inequality. Survey items are rendered as nodes of a network whose undirected and weighted edges are estimated from real data. Ties represent symmetrical and causal influence between evaluative reactions. The construct of attitudes towards inequality coincides with the network of evaluative reactions.

## Hypotheses

Research applying the CAN model has consistently produced two findings which will be assessed in this paper. As introduced earlier, attitude networks are structured by two opposite tendencies. Indeed, individuals are motivated to achieve both a consistent and accurate representation of the attitude object. As a consequence, attitude networks form clusters of nodes in which aligned evaluative reactions gather, whereas unaligned items are more likely to belong to different communities. However, these clusters are still embedded in the same network structure since they are often connected by shortcuts, which means that even if two nodes belong to different substructures it is still possible to connect them through a small number of steps [(Dalege et al., 2016; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=12243635824561772&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:7d183f8f-3926-411e-b1c5-4d2005fe8777,c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). This implies that attitude networks are simultaneously characterized by high clustering and high connectivity. Connectivity measures the extent to which network nodes are linked to each other. Highly connected networks are cohesive structures where information flows quickly, and where nodes strongly influence each other. Importantly, real-world social networks display both high clustering and high connectivity. To describe these systems of relationships, scholars usually adopt the small-world metaphor (Watts & Strogatz, 1998). Empirically, a small-world structure was observed for attitude networks measuring attitudes towards political candidates [(Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017; Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=7272930934578034&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:5b2491db-b30c-4f58-ab39-c2c7471d3c9c,c61b91da-fa6e-4348-80b6-c2428280b16a:7d183f8f-3926-411e-b1c5-4d2005fe8777,c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699), political values [(Turner-Zwinkels & Brandt, 2022)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=7419011195454444&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:e5df995a-5b3c-4248-922e-78ca10ebdc1d), post-national citizenship identities [(Schlicht-Schmälzle et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=24359055766111648&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:6a9141c6-6628-4444-8af4-2a3e13440629), job satisfaction [(Carter et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=41032302182289526&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:cbee107f-f476-44cf-ac6c-c76e7fb5ee99), and bio-based plastic [(Zwicker et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=34854808005247995&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:8c732dff-5588-4161-b313-520864427349). Here we test whether attitudes towards inequality are characterized by the same features.

*H1: The network of attitudes towards inequality will show a small-world structure*

Moreover, the CAN model has relevant implications for the dynamics of attitudes. Nodes of a network vary in importance, and this is captured by the centrality metric. Relevant nodes are more influential in the attitude network because they are involved in stronger and/or more interactions than peripheral nodes. This generates a predictive hypothesis regarding attitude change. Indeed, if a change occurs in a central -rather than peripheral node- the attitude network should vary to a greater extent. This intuition was confirmed by simulation and longitudinal studies. In simulated data, changes in central nodes were associated with a downstream effect in the attitude networks [(Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=8398537729577212&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:7d183f8f-3926-411e-b1c5-4d2005fe8777,c61b91da-fa6e-4348-80b6-c2428280b16a:5b2491db-b30c-4f58-ab39-c2c7471d3c9c). The downstream effect occurs when a change in the state of a node (i.e.: from “not endorsed” to “endorsed”) produces adaptations in the network, leading other neighboring nodes to change their state consistently. Peripheral nodes did not trigger these wider adjustments. This phenomenon was also observed, even if with lesser intensity, with longitudinal data in the field of job satisfaction [(Carter et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=29290126480480594&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:cbee107f-f476-44cf-ac6c-c76e7fb5ee99), and COVID-19-related attitudes [(Chambon, Dalege, et al., 2022; Chambon et al., 2023; Chambon, Kammeraad, et al., 2022)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=7492797912659419&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:dd32862c-e62c-42a8-90f0-1a6b06bbb409,c61b91da-fa6e-4348-80b6-c2428280b16a:d318829d-ff0c-465e-bc63-02415fe27799,c61b91da-fa6e-4348-80b6-c2428280b16a:81770833-0752-4aff-ba6d-0ae56359cdf0). Here we simulate a manipulation attempt targeting each node in the network to test wheater:

*H2: Changes in central - rather than peripheral - nodes in the network of attitudes towards inequality are associated with downstream effects.*

# Methods

## Data and sample

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)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=725251600011309&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:55247836-2119-4954-9b7e-8624e750a156) offers this possibility, as it includes questions concerning perceptions, beliefs, and judgments about not only inequality, but also taxation, and redistribution. We use Italian data, representative of the Italian population aged 18 years or older. Originally the sample consists of 1,215 individuals in total. After listwise deletion, we work with a subsample of 1,009 individuals for the network estimations and simulation.

## Variables

Following the operationalization proposed by Janmaat [(2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=29322039976123504&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a&options=%7B%22items%22%3A%7B%220a3c846c-7570-4913-bd72-3afd46468081%3Aa5fe0957-21b3-4f66-991b-a1b55320ca5a%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D), we account for the multidimensionality of attitudes towards inequality by measuring it through perceptions, beliefs, and judgments. Considering the aforementioned close relationship between inequality, taxation, and redistribution, we use evaluative reactions in all three domains. Table 1 shows the selected variable 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. Lastly, since the CAN model operates with dummy variables, we dichotomize each variable. Therefore values 1 indicate the endorsement of each evaluative reaction, whereas values 0 indicate their rejection.

### Perceptions

Taking into account the data availability, we measure perceptions of unequal distribution of resources, large income inequality, and tax regressivity. Perception of unequal distribution of resources is measured using a 5-point scale showing five distributional pyramids. Individuals have to choose which diagram most closely approximates the distribution of resources in Italy. We code the first three pyramids, which have a more unequal configuration, as values 1, and the remaining two, which are more equal, as 0. The perception of large income inequality is addressed by the commonly used variable concerning people's agreement with the statement that "Income differences in Italy are too large". The value 1 represents people who “Agree” and “Strongly agree”, while the value 0 refers to “Neither agree nor disagree”, “Disagree” or “Strongly disagree” answers. Perceived tax regressivity refers to people who think that taxes in Italy for high-income earners are “much too low” or “too low”, with answers “about right”, “too high” or “much too low” coded as 0.

Table 1: Variables and questions

| **Dimension** | **Evaluative reaction** | **Variable** | **Question** | |
| --- | --- | --- | --- | --- |
| Perceptions | Perception of unequal distribution of resources  Perception of large income inequality  Perception of tax regressivity | p\_ineq  p\_inc\_ineq  p\_tax | These five diagrams show different types of society. What type of society is Italy today – which diagram comes closest?  To what extent do you agree or disagree with the following statement: Differences in income in Italy are too large.  Generally, how would you describe taxes in Italy today for those with high incomes? | |
| Beliefs | Belief in equal distribution of resources  Belief in progressive taxation  Belief in public redistribution  Belief in market redistribution | b\_ineq  b\_tax  b\_red\_pub  b\_red\_mar | These five diagrams show different types of society. What do you think Italy ought to be like?  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?  It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes.  It is the responsibility of private companies to reduce the differences in pay between their employees with high pay and those with low pay. | |
| Judgments | Judgment about existing unfair distribution  Judgment about political disinterest in redistribution  Judgment about the failure of public redistribution | j\_ineq  j\_red\_unca  j\_red\_fail | How fair or unfair do you think the income distribution is in Italy?  Most politicians in Italy do not care about reducing the differences in income between people with high incomes and people with low incomes.  How successful do you think the government in Italy is nowadays in reducing the differences in income between people with high incomes and people with low incomes? | |

Source: Own elaboration.

### Beliefs

We include indicators measuring beliefs on ideal inequality, public redistribution, market redistribution, and progressive taxation. The variable for belief in equal distribution of resources is constructed from the ISSP question in which people are presented with the aforementioned pyramid diagrams, now asking which one Italy ought to be. We code the last two pyramids, which have a more egalitarian configuration, as value 1, and the remaining three, which are more unequal, as 0. Belief in progressive taxation refers to whether people with high incomes should pay a larger share of taxes than people with low incomes ("Much larger share", "Larger" = 1; "The same share", "Smaller", "Much smaller share" = 0). Belief in public redistribution refers to the degree to which individuals agree that it is the government's responsibility to reduce income differences between high-income earners and low-income earners ("Strongly agree", "Agree" = 1; "Neither agree nor disagree", "Disagree", "Strongly disagree" = 0). Lastly, belief in market redistribution indicates agreement that it is the responsibility of private firms to reduce wage differentials between high and low-wage workers ("Strongly Agree", "Agree" = 1; "Neither Agree nor Disagree", "Disagree", "Strongly Disagree" = 0).

### Judgments

Regarding judgments, we include three evaluative reactions: existing unfair inequalities, political disinterest in redistribution, and failure of public redistribution. The first measures how fair individuals consider the distribution of income in Italy ("Very unfair", "Unfair" = 1; "Fair", "Very fair" = 0). The second measures agreement with the idea that most politicians in Italy do not care about reducing differences between high and low income people ("Strongly agree", "Agree" = 1; "Neither agree nor disagree", "Disagree", "Strongly disagree" = 0). Finally, the judgment about the failure of public redistribution refers to the agreement that the government in Italy is unsuccessful today in reducing income differences between high and low income earners ("Very little success", "Fairly little success" = 1; "Neither success nor failure", "Fairly successful", "Very successful"= 0).

## Network estimation

Testing H1 requires the estimation of an attitude network. A cross-sectional network estimation outputs the between-person structure of attitudes towards inequality. We apply a Pairwise Markov Random Fields [PMRF] model to ISSP data in order to translate the joint probability distribution of a set of variables in a network [(Borsboom et al., 2021)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=3003143663603596&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:77902d13-3eed-470a-a4fc-1d0e839ca6bb). PMRFs are parsimonious graphical models describing conditional associations between these items (Laurizen, 1996; Murphy, 2012). Edges of a PMRF can be interpreted as partial correlation coefficients, meaning that two variables are connected if statistically dependent, and unconnected if conditionally independent after controlling for the other variables in the model. Moreover, edges are undirected and weighted, thus suitable to be applied to the CAN model. PMRF can be estimated from dichotomous [(Borkulo et al., 2015)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9562038749744506&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:f863500f-bae2-42e4-95e7-646da824636f), continuous [(Epskamp, Waldorp, et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=23032364689795048&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:186fe824-a832-409a-ba25-0d8aa0ee2418), and mixed data [(Haslbeck & Waldorp, 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=45411410464411794&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:633ef322-7aeb-4178-852a-5ee3fd70b73d). Network estimation differs in each of these cases, but the interpretation of network edges does not differ [(Borsboom et al., 2021)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9067978465252905&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:77902d13-3eed-470a-a4fc-1d0e839ca6bb). The CAN model has not yet been implemented for continuous or mixed data types.

Therefore, the attitude network is estimated with the eLasso procedure, which operates with dummy variables [(Borkulo et al., 2015)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=3497911040143702&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:f863500f-bae2-42e4-95e7-646da824636f). This technique fits a loop of logit regressions in which each variable is iteratively regressed on each other while controlling for every other variable in the model. This operation entails dealing with multicollinearity and with a statistical problem of considerable size. Therefore, eLasso employs regularization (Tibshirani, 1996). This requires setting a tuning parameter that adjusts the sparsity of the resulting network, that is, the extent to which weak edges of the network are suppressed to "zero". Regularization enhances the parsimony of the model, reduces the risk of including spurious edges, and facilitates the interpretation of the attitude network [(Epskamp, 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=8626640466541317&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:0c4bd602-bde8-49c8-be81-31eb7511306d). The optimal value of the tuning parameter is obtained by minimizing the Extended Bayesian Information Criterion (Chen & Chen, 2008). As a final step, eLasso averages the estimates obtained through the set of logit regressions and encodes them into network edges of different widths and colors. Edge thickness is indicative of the magnitude of the underlying association. In the following, red edges indicate negative associations and blue positive ones.

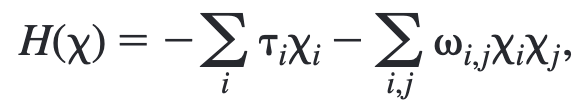
Once the attitude network is estimated we study its global and local properties. We apply the Walktrapp community algorithm to identify network clusters [(Pons & Latapy, 2005)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=43358205879264433&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:347321e6-c9f6-4f3e-8787-a8337843c5e0). For each node, we further calculate the “strength” centrality metric, by summing the absolute values of the edge weights of all ties in which the node is involved [(Opsahl et al., 2010; Pons & Latapy, 2005)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=8896853562690569&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:347321e6-c9f6-4f3e-8787-a8337843c5e0,c61b91da-fa6e-4348-80b6-c2428280b16a:f31b5001-2e73-49ee-9a91-383651b2a48e). Edges and centrality scores are inferred from survey data. Thus, it is important to quantify their robustness with non-parametric bootstrapping techniques [(Epskamp, Borsboom, et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=6903059771554847&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:1d710043-b7c6-4fa1-93a5-7aa13c36cd98). Specifically, we build bootstrapped confidence intervals around the point estimate of each edge, and we assess the stability of the centrality scores by calculating 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, we carry out *bootstrapped difference tests* to assess whether differences in edge weights and centrality scores are statistically significant (ibid.).

To test the small-worldness of the network we implement the statistical test proposed by Humphries and Gurney [(2008)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=36441860769973244&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:b3a24846-5dd3-467f-87d3-147be14a01dc&options=%7B%22items%22%3A%7B%22c61b91da-fa6e-4348-80b6-c2428280b16a%3Ab3a24846-5dd3-467f-87d3-147be14a01dc%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D), 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. 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 [(Humphries & Gurney, 2008)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=11011057818717929&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:b3a24846-5dd3-467f-87d3-147be14a01dc). Formally, a network is said to be a small-world network if the test produces a value greater than 1.

## Network simulation

To test H2 we simulate a series of successful persuasion attempts targeted at each evaluative reaction. The dependent variable of this simulation is the sum score of all evaluative reactions, measured before and after each manipulation. H2 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.

Longitudinal applications of attitude networks conform to the Ising model (Ising, 1925), which originated in the field of ferromagnetism, although being applied to predator-pray dynamics, neuroscience, and clinical psychology [(Dalege et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9262668734505092&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:12564573-44ed-454b-a58b-80c7e2932eec). In this model, 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 an evaluative reaction [(Dalege et al., 2016, 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=8814655076242319&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:12564573-44ed-454b-a58b-80c7e2932eec,c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699); van Borkulo et al. 2014). Three parameters regulate the overall configuration of an attitude network. The temperature parameter governs the entropy of the system. This variable is held constant in all simulations. Two other parameters are described by the Hamiltonian function, which estimates the amount of energy expenditure of a given network configuration:



Each evaluative reaction (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.

To address H2 we rely on research designs that have been applied in other works simulating attitude change [(Dalege, Borsboom, Harreveld, & Maas, 2017; Schlicht-Schmälzle et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=49263609296595445&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:6a9141c6-6628-4444-8af4-2a3e13440629,c61b91da-fa6e-4348-80b6-c2428280b16a:5b2491db-b30c-4f58-ab39-c2c7471d3c9c). We operationalized a manipulation attempt targeting one node as an increase in its threshold. We start the simulation by creating ten samples of 3000 individuals answering the survey items in Table 1. Differences in the values of their responses are generated by differences we set in the values of node thresholds. We first build a baseline sample in which all nodes have a moderately negative threshold (-0.1); then we simulate survey answers according to the prediction of the Ising model. Next, we construct the other ten datasets by iteratively setting the threshold of one node at a time to a high value (+1), while all others maintain their moderately negative threshold (-0.1). From these data, we estimate ten attitude networks as specified in the previous paragraph. We also calculate one additive index per network, by summing the values of the state of each of its nodes. Hence, the sum scores range between -10 (all evaluative reactions are not endorsed) and +10 (every item is endorsed). Finally, we plot them to understand whether manipulation attempts of the same strength are associated with changes of different intensities in the global structure of the network.

## Statistical analyses

We perform all analyses in RStudio (RStudio Team, 2020). We prepare and clean the data with *dplyr* (Wickham et al., 2023). We estimate the attitude network with the *IsingFit* package (Borkulo & Epskamp, 2016). For community detection, calculation of centrality metrics, and network visualization we rely on *qgraph* (Epskamp et al., 2012). The small-world test is part of the *NetworkToolbox* package (Christensen, 2018). The simulation uses the *IsingSampler* package (Epskamp, 2015). Figures regarding the results of the simulation and node centrality are plotted with *ggplot2* (Wickham, 2016). With *bootnet* we perform robustness analyses and specific tests for detecting differences in edge weights and centrality (Epskamp, Borsboom & Fried, 2017).

# Results

## Network estimation

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.

Table 2: Descriptive statistics

| **Variable** | **N** | **Mean** | **SD** | **Min** | **Max** |
| --- | --- | --- | --- | --- | --- |
| p\_ineq  p\_inc\_ineq  p\_tax  b\_ineq  b\_tax  b\_red\_pub  b\_red\_mar  j\_ineq  j\_red\_unca  j\_red\_fail | 1,009  1,009  1,009  1,009  1,009  1,009  1,009  1,009  1,009  1,009 | 0.714  0.954  0.188  0.699  0.833  0.866  0.628  0.954  0.871  0.783 | 0.452  0.209  0.391  0.459  0.374  0.341  0.483  0.209  0.335  0.412 | 0  0  0  0  0  0  0  0  0  0 | 1  1  1  1  1  1  1  1  1  1 |

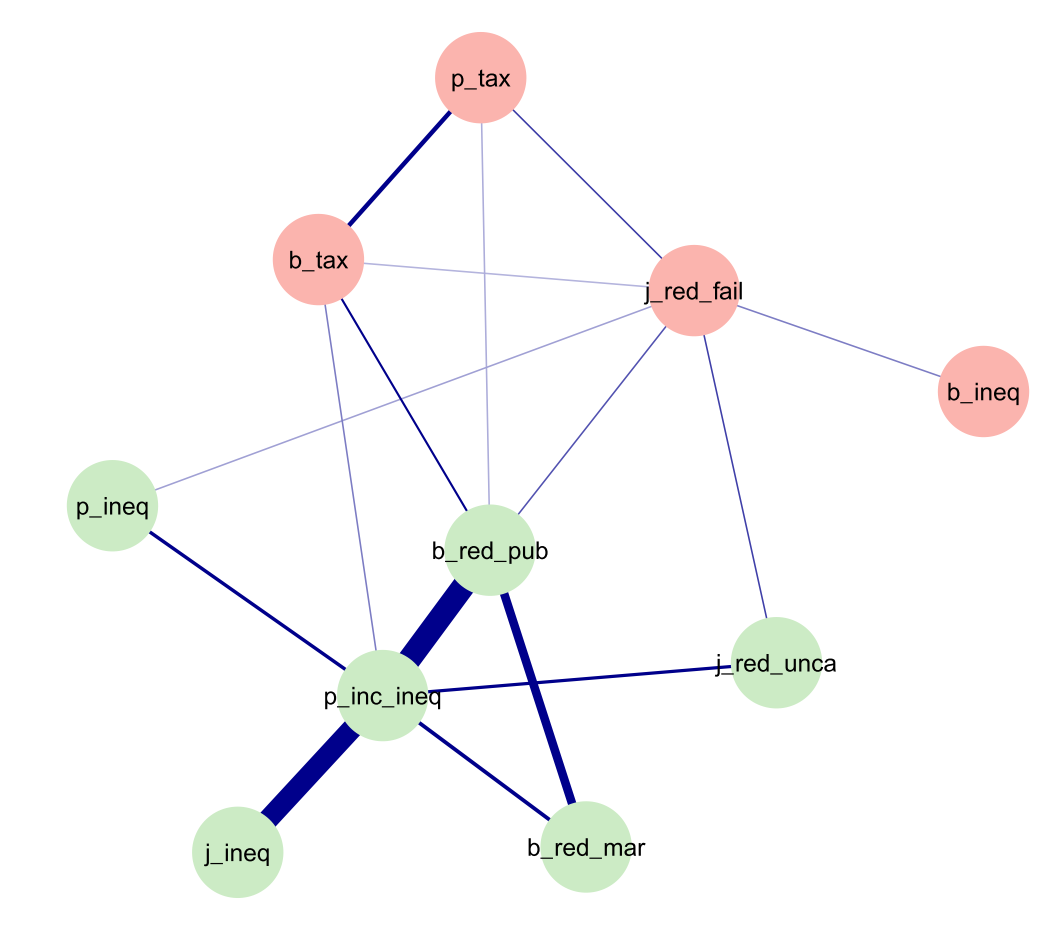
Source: Own elaboration.

Figure 3 shows the network of attitudes towards inequality in Italy. The ten evaluative reactions of Table 2 form a single network, which means that none of them is conditionally independent of the others. Connections between these nodes are interpretable as positive partial correlations since no red edges are detected. Therefore high perceptions, egalitarian beliefs, and critical judgments about inequality, redistribution, and taxation are all positively associated in Italy. Edge weights are the aggregation of logit regression coefficients, and range between 0.236 and 1.699. The weakest association is between belief in progressive taxation (*b\_tax*) and judgment about the failure of public redistribution (*j\_red\_fail*). The strongest association involves perception of large income inequality (*p\_inc\_ineq*) and belief in public redistribution (*b\_red\_pub*). Perception of large income inequality is also strongly associated with judgment about existing unfair distribution (*j\_ineq*). Indeed, a bootstrapped difference test reveals no statistically significant differences between the edge weight of the tie *p\_inc\_ineq - b\_red\_pub* (mean [M] = 1.697, confidence interval at 95% [CI]: 0.948 - 2.550) and that of *p\_inc\_ineq - j\_ineq* (M = 1.520, CI: 0.474 - 2.714).

Nodes are colored according to their community membership. We detect two clusters. The green one features Perception of unequal distribution of resources (*p\_ineq*), perception of large income inequality (*p\_inc\_ineq*), belief in public and market redistribution (*b\_red\_pub*, *b\_red\_mar*), judgment about existing unfair distribution (*j\_ineq*), and judgment about political disinterest in redistribution (*j\_red\_unca*). The second one gathers perception of tax regressivity (*p\_tax*), belief in progressive taxation (*b\_tax*), belief in equal distribution of resources (*b\_ineq*), and judgment about the failure of public redistribution (*jud\_red\_fail*). It is important to note that clusters represent subsets of network nodes that are more likely to interact with vertices of the same substructure, rather than with outsiders. Thus, clustering indicates that perceptions, judgments, and beliefs do not form separate clusters, meaning that items measuring different dimensions of attitudes towards inequality mutually interact without strict boundaries.

In Italy, perception of large income inequality (*p\_inc\_ineq*) is positively and strongly related to both support for public redistribution (*b\_red\_pub*) and judgment about existing unfair distribution (*j\_ineq*), as they are part of the same community and are linked by the strongest ties in the network. In addition, perception of large income inequality (*p\_inc\_ineq*) is also associated with perception of unequal distribution of resources (*p\_ineq*), but the latter is not tied to either belief in public redistribution (*b\_red\_pub*) or judgment about inequality (*j\_ineq*). Perceiving high income inequality (*p\_inc\_ineq*) is also associated with both belief in market redistribution (*b\_red\_mar*) and judgment about political disinterest in redistribution (*j\_red\_unca*). Beliefs in public and market redistribution (*b\_red\_pub, b\_red\_mar*) are also positively linked with moderate intensity. Perception and belief about taxation (*p\_tax, b\_tax*) are moderately associated too. However, they are not closely related to how individuals perceive and judge existing inequalities (*p\_ineq, p\_inc\_ineq, j\_ineq*). Indeed, evaluative reactions towards taxes (*p\_tax, b\_tax*) tend to be more related to belief and judgment about public redistribution (*b\_red\_pub, j\_red\_fail)*: endorsing the perception of taxation regressivity (*p\_tax*) increases the likelihood of endorsing both belief in progressive taxation (*b\_tax*) and judgment about the failure of public redistribution (*j\_red\_fail*), and vice versa. Finally, belief in equal distribution of resources (*b\_ineq*) only weakly interacts with critical judgment about the effectiveness of public redistribution (*j\_red\_fail*).

Figure 3: The network of attitudes towards inequality

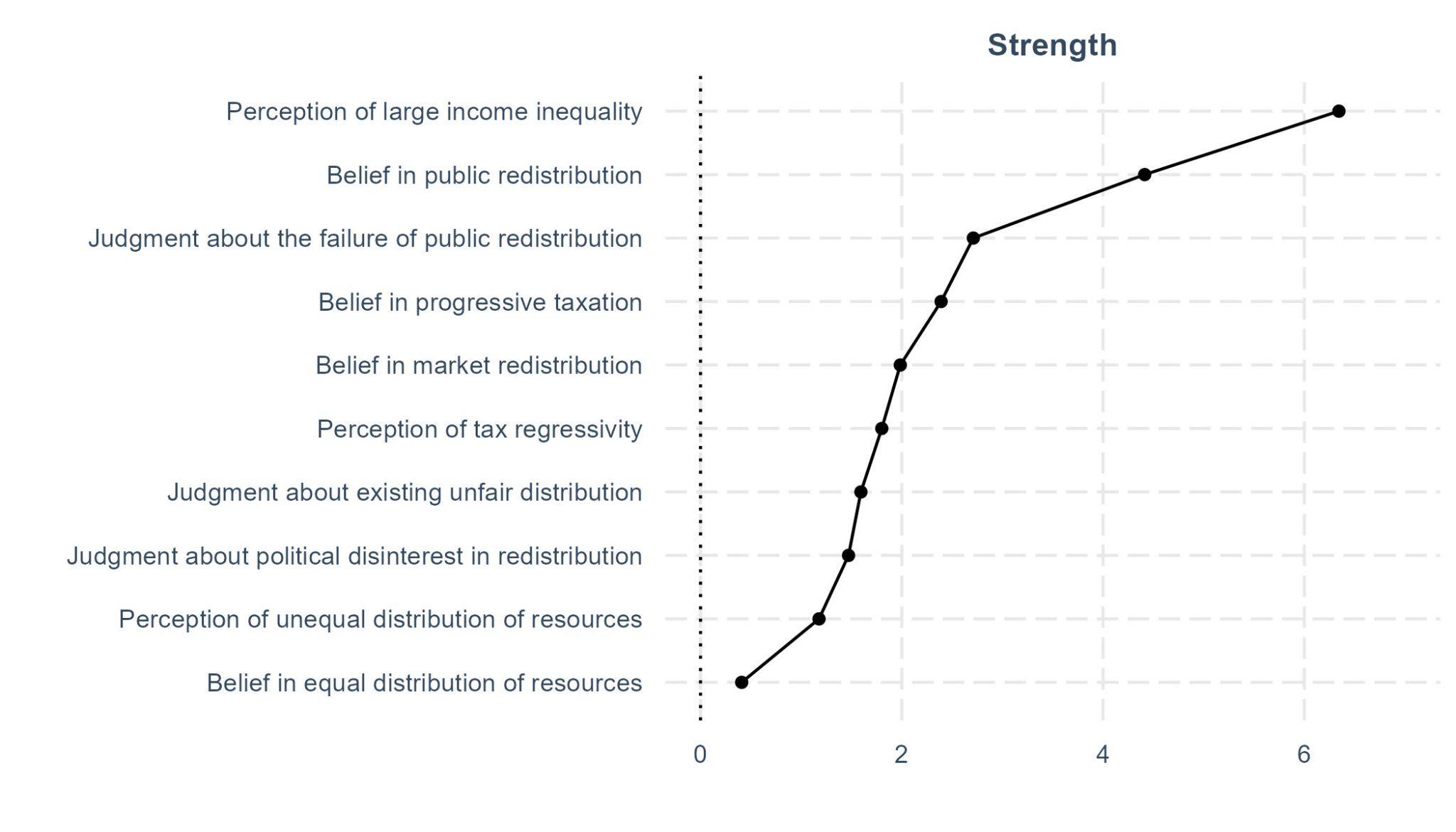


Notes: Nodes represent ten evaluative reactions regarding attitudes towards inequality. An edge is drawn when two variables are correlated, after having controlled for the others. The absence of an edge between two variables means that they are conditionally independent. Blue [red] edges represent positive [negative] associations; thicker edges represent stronger relationships. The color of the nodes corresponds to the detected communities in each network. Node names: perception of unequal distribution of resources (*p\_ineq*), perception of large income inequality (*p\_inc\_ineq*), perception of tax regressivity (*p\_tax*), belief in equal distribution of resources (*b\_ineq*), belief in progressive taxation (*b\_tax*), belief in public redistribution (*b\_red\_pub*), belief in market redistribution (*b\_red\_mar*), judgment about existing unfair distribution (*j\_ineq*), judgment about political disinterest in redistribution (*j\_red\_unca*), judgment about the failure of public redistribution (*j\_red\_fail*).  
Source: Own elaboration.

Figure 4 reports the centrality Strength scores of each node. For each node, this metric is calculated by summing all edge weights of its ties. Consequently, its calculation incorporates uncertainty related to the estimation of the edge weights. Therefore, we calculate the Correlation stability coefficient [CS] coefficient to check the robustness of this measure. We find a CS coefficient of 0.283, which is higher than the conventional minimum threshold of 0.25. This means that even if we drop almost 30% of the cases, we have a 95% probability of obtaining centrality values that correlate 70% with the original ones. Therefore, centrality scores are robust to sampling variation. Being involved in the strongest relationships, the nodes *p\_inc\_ineq* and *b\_red\_pub* are at the top of the table, with raw Strength scores of 6.344 and 4.414 respectively. A difference test for centrality scores shows no differences between their mean values across the bootstrapped samples (for *p\_inc\_ineq*: bootstrapped M = 5.864, CI: 3.616 - 9.071; for *b\_red\_pub*:bootstrapped M =4.894, CI: 2.625 - 6.202). Moreover, the Strength scores of these two nodes do not statistically differ from that of *j\_red\_fail* (bootstrapped M = 2.935, CI: 1.151 - 4.270). However, the centrality of the most central node (*p\_inc\_ineq*) statistically differs from that of the fourth entry in the table (*b\_tax*) and from the ones below. Furthermore, it is interesting to compare the determinants of these scores. Perception of income inequality and belief about public redistribution are important in the network also because of the strong association they share. In particular, *p\_inc\_ineq* shares important connections with *j\_ineq* and *b\_red\_pub.* Similarly, the node *b\_red\_pub* is associated with a high score mainly because of the edge *b\_red\_pub - p\_inc\_ineq.* In contrast, the node *j\_red\_fail* is central by virtue of its numerous connections of weak intensities. Indeed, this judgment is not strongly related to any other evaluative reactions, but interacts with six other nodes (*p\_tax*, *b\_tax*, *p\_ineq*, *b\_red\_pub*, *j\_red\_unca*, and *b\_ineq*). In the next section, we will examine how the different determinants of centrality scores - magnitude and amount of associations - relate to attitude change.

Finally, we test if the attitude network in Figure 3 possesses small-world characteristics. Recall that the attitudes towards inequality network is proposed to show this structure as a consequence of two opposite socio-psychological tendencies. The need for cognitive consistency should lead evaluative reactions to align their state. In contrast, the need for accuracy should produce greater misalignment, prompting individuals to respond to survey items related to judgments, perceptions and beliefs about inequality differently. Therefore, we apply the small world-test proposed by Humphries and Gurney [(2008)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9686559988107254&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:b3a24846-5dd3-467f-87d3-147be14a01dc&options=%7B%22items%22%3A%7B%22c61b91da-fa6e-4348-80b6-c2428280b16a%3Ab3a24846-5dd3-467f-87d3-147be14a01dc%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D) to see if the structure of the CAN network conforms to those detected by other works operating with this model. The test simulates a thousand random networks of the same size of the attitude network (ten nodes). It then averages the estimates of the connectivity and clustering coefficients obtained from these. Surprisingly, the test yields a small-world value of 0.836, rejecting H1. The average clustering coefficient of the random networks is 0.425, while the average shortest path length is 1.824. The network of attitudes toward inequality has both lower connectivity (1.777) and lower clustering coefficient (0.346), meaning that its structure does not conform to the hypothesized one.

Figure 4: Centrality table of the network of attitudes towards inequality



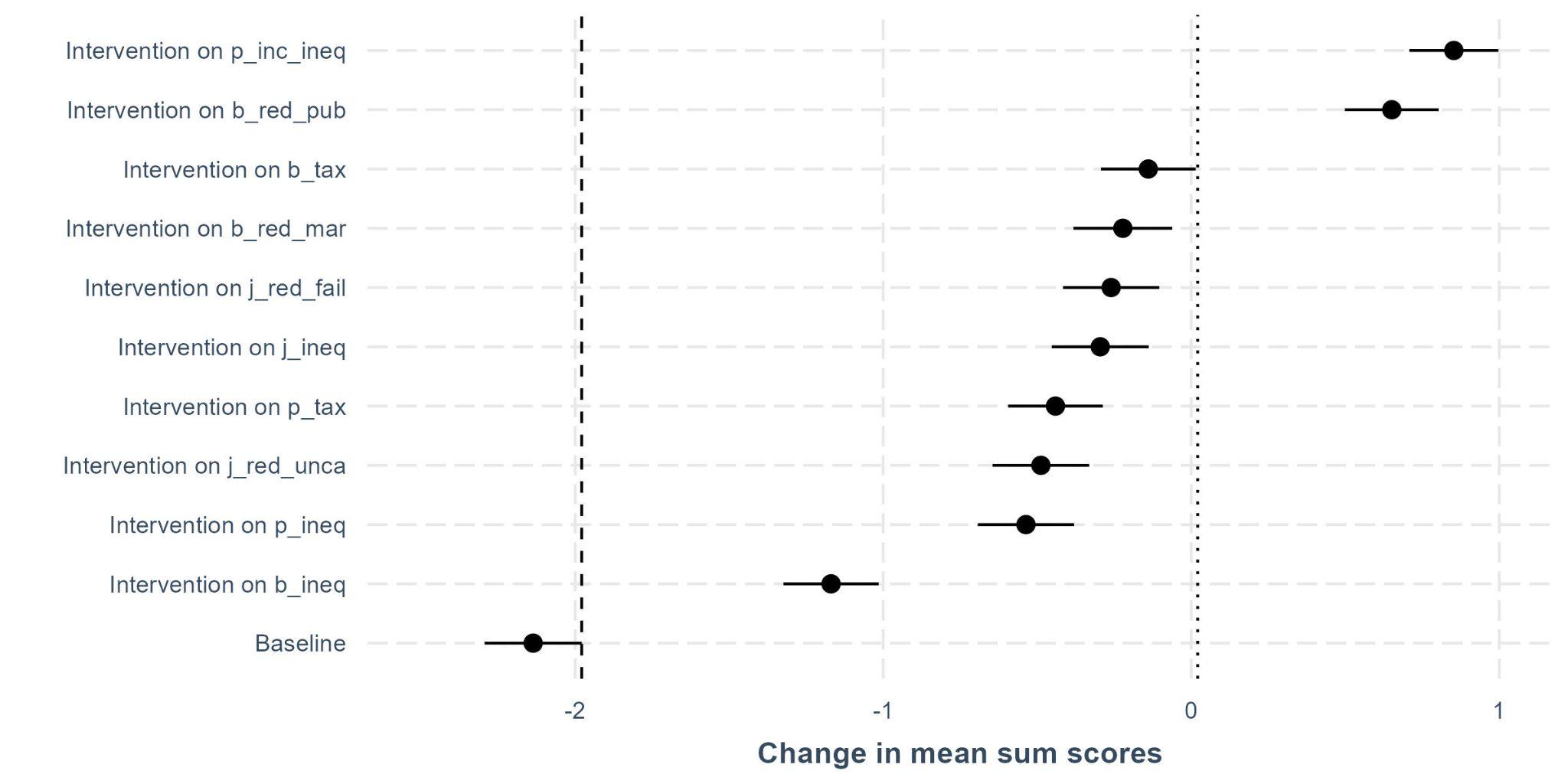
Source: Own elaboration.

## Simulating attitudinal changes

To test H2 we simulate ten different manipulation attempts that influence each node in the network at a time. Manipulation attempts are modeled as an increased value of the threshold of the targeted node (from 𝛕 = -0.1 to 𝛕 = +1), while keeping the others fixed at a moderately negative value (𝛕 = -0.1). Note that according to the Hamiltionian function, reported in the method section, the change in the threshold value of a given node is not automatically reflected in the change of its state. Indeed, nodes are embedded in a network, and their state is also determined by the parameter ω. This means that changing 𝛕 from -0.1 to 𝛕 = +1 only increases the probability that a given node will assume the state +1. However, this is a probabilistic prediction rather than a mechanical one. For example, a node with 𝛕 = +1 could become negatively linked with other nodes, and this can in turn exercise a pressure on it to remain in the state -1. Therefore, by manipulating node thresholds we are not directly determining the state of any node.

The forest plot in Figure 5 reports the results of H2. The simulation involves re-estimating a cross-sectional attitude network at Time 0. Here all thresholds are set to a moderately negative value (𝛕 = -0.1). Next, we label this as the baseline network, and we calculate its sum score as specified in the Methods section. In the figure, this sum score is represented as a dot, and the upper boundary of its confidence interval dictates the position of the baseline reference line on the left. This line indicates if sum scores obtained from the manipulated networks estimated at Time 1 statistically differ from the baseline value. Indeed, each other dot in Figure 5 represents the value of the sum score produced in ten samples that are targeted with different manipulation attempts. These manipulations target the nodes in Figure 3, whose centrality scores are given in the centrality table in Figure 4. Therefore, we predict that the most central nodes trigger a downstream effect. This consists of an adaptation process in which the state change of a given node leads to the state change of neighboring ones. To facilitate the detection of this effect, we insert a second reference line in the right part of Figure 5. We obtain this line adding two units to the value of the upper boundary of the confidence interval of the baseline sum score. This is because in the simulation states are either -1 or +1. Hence, we observe a downstream effect only when the sum score of a manipulated network changes by more than two units with respect to that of the baseline, meaning that a manipulation of node’s thresholds produces not only a change of its state, but also wider adjustments in the network structure.

Figure 5: Changes in mean sum scores of simulated networks



Notes: *Baseline*: no intervention, all nodes with weakly negative thresholds. *Intervention*: simulation of a persuasion attempt targeting a single node; other nodes retain weakly negative thresholds. Intervals that are to the right of the first reference line are indicative of successive manipulation attempts. Intervals that are to the right of the second one are indicative of downstream effects.

Source: Own elaboration.

Since in the baseline sample all thresholds are moderately negative, the sum score of the baseline network is moderately negative (M = -2.137; CI: -2.294 - -1.979). All manipulations produce effects, as all other sum scores are to the right of the first reference line. The lowest sum scores are that of the networks simulating manipulations of the nodes *b\_ineq*, *p\_ineq*, *j\_red\_unca*. This is consistent with H2, since these nodes are the least central in the network. Only the two most central nodes produce downstream effects: *p\_inc\_ineq* (M = 0.852; CI: 0.708 - 0.997) and *b\_red\_pub* (M = 0.651; CI: 0.499 - 0.804). As discussed in the previous section, both perception of large income inequality (*p\_inc\_ineq*) and belief in public redistribution (*b\_red\_pub*) play an important role in the network. Therefore, when their thresholds change this is firstly related to their state transition, and then reflected in the adaptation of neighboring nodes. In both cases, the magnitude of the downstream effect is moderate. The mean scores of the baseline network differ by slightly more than two units from those of the other two samples. These changes represent approximately a 15 percent increase in the probability of supporting high perceptions, egalitarian beliefs, and unfair judgments about inequality, redistribution, and taxation.

# Discussion

In this article, we selected ten evaluative reactions measuring individual perceptions, beliefs, and judgments towards inequality, redistribution, and taxation. All these items formed a fully connected attitude network. Within this network, nodes gather in two communities. Theoretically, attitudes towards inequality are described as composed by three dimensions -perception, beliefs, and judgments [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=689145617558993&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a). However, network communities do not respect this structure, since evaluative reactions measuring each of these dimensions interact and form communities regardless of their nature. Similarly, variables referring to the three topics we mentioned above - inequality, redistribution, and taxation- do not form different communities. This indicates that attitudes towards inequality are indeed a multidimensional and multifaced construct, and that network models are important in doing justice to this complexity.

Perception of income inequality (*p\_inc\_ineq*), belief in public redistribution (*b\_red\_pub*), and judgment about its failure (*j\_red\_fail*) are the most central nodes in the network of attitudes towards inequality in Italy. 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. Alesina & Giuliano, 2009; Janmaat, 2013; Kuhn, 2011, 2019; Lübker, 2004; Shepelak & Alwin, 1986)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=9807829504778398&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:22b79c2d-0357-461c-8471-0cbc1d7f2a51,0a3c846c-7570-4913-bd72-3afd46468081:937818c3-ea7a-4cbe-9f62-3fa0e1d957aa,0a3c846c-7570-4913-bd72-3afd46468081:e139e873-ed74-4984-9c94-e020458801d6,0a3c846c-7570-4913-bd72-3afd46468081:6b398ebd-b724-467e-a08c-215a2c6488a4,0a3c846c-7570-4913-bd72-3afd46468081:ebe87e67-14af-45a0-a8e2-886516edc9f6,0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a,0a3c846c-7570-4913-bd72-3afd46468081:ebc9b3ce-ff9a-4ea2-bacd-35c39c722975). Indeed, perceived income inequality was found to be a strong predictor of belief in public redistribution in several contexts [(García‐Sánchez et al., 2020; Trump, 2023)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=4713099799348268&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:2d93587f-9510-4e10-b201-fde8c4b1b3a7,0a3c846c-7570-4913-bd72-3afd46468081:548f8074-084b-410b-816d-44ea49789c66). Furthermore, perceived inequality is even more important than objective inequality in predicting redistributive preferences across contemporary societies [(Bussolo et al., 2021; Trump, 2023)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=5621334080208055&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:548f8074-084b-410b-816d-44ea49789c66,0a3c846c-7570-4913-bd72-3afd46468081:e1beb8e5-0fbb-4ea2-a5d6-179be00ba4df). The fact that high perception of income inequality is the most central node of the network is due to its strong links with both perception and judgment about the distribution of resources. This confirms concerns in the literature that argues that its measurement[[4]](#footnote-3) simultaneously gauges people's perceptions and judgments on distributional issues (Castillo et al., 2022; Heiserman & Simpson, 2021). This insight may also explain the absence of a direct relationship between judgment about unfair existing inequality and belief in public redistribution, previously found in the literature [(Ahrens, 2020)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=15448963426605&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:bcf2c5f2-4cf7-4263-9207-de72d6f5625d). In the attitude network, this relationship is instead mediated by the perception of income inequality, confirming its dual nature. Finally, the judgment of government failure in redistribution is the third most central node in the network. Consistently, it has already been shown that trust in the political system has a strong influence on the level of support for public redistribution [(Franetovic & Castillo, 2022)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=006394117699705548&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:f8983209-47e6-42dd-9f21-1f84856762c4) and the formation of political perceptions [(Stevens, 2016)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=018106384371932016&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:ce70a001-4837-46b2-846a-5a8777b79e1a).

Perception and belief about the distribution of resources (*p\_ineq, b\_ineq)* are the least central nodes on how people understand inequality in Italy. Even more surprising is the fact that perception (*p\_ineq)*, belief *(b\_ineq)* and judgment *(j\_ineq)* about resource distribution are associated with each other, but only through the intermediation of other evaluative reactions -such as judgment about the government's failure to redistribute resources. At first glance, this might lead to hasty conclusions regarding their operationalization, which relies on distribution pyramidal diagrams. However, it is important to consider that the estimation of our network involves procedures such as the dichotomization of variables and the edge shrinkage due to eLasso regularization. The fact that our network accounts for only the strongest links between its nodes could hide existing relationships between perception, belief and judgment about the distribution of resources. The intermediary role of other variables highlights the need in the distributive justice literature to study mediating or moderating factors, in line with the work of García‐Sánchez and colleagues [(2020; 2022)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=5431737024985273&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:2d93587f-9510-4e10-b201-fde8c4b1b3a7,0a3c846c-7570-4913-bd72-3afd46468081:7e04b1c0-c0f4-44f6-b447-6c5d7c78d174&options=%7B%22items%22%3A%7B%220a3c846c-7570-4913-bd72-3afd46468081%3A2d93587f-9510-4e10-b201-fde8c4b1b3a7%22%3A%7B%22suppressAuthor%22%3Atrue%7D%2C%220a3c846c-7570-4913-bd72-3afd46468081%3A7e04b1c0-c0f4-44f6-b447-6c5d7c78d174%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D)

Structurally, evaluative reactions should form a small-world network to balance the need for consistency and the need for accuracy [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=16523989033196496&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). However, the network of attitudes towards inequality does not conform to such a structure[[5]](#footnote-4). Empirically, a small-world attitude network has been found in several contributions. Yet, a closer examination of these results shows a more complex scenario. An early contribution [(Dalege et al., 2016)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=5402256003006073&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699) found that items measuring the perceived properties of a political candidate form a small-world network[[6]](#footnote-5). Another work examined attitudes toward job satisfaction and found evidence of this structure [(Carter et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=4797662993296664&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:cbee107f-f476-44cf-ac6c-c76e7fb5ee99). However, when the sample was split by sociodemographic characteristics and the network was re-estimated, the tests showed more unstable results[[7]](#footnote-6). Another research found the small-worldness of attitudes towards postnational citizenships[[8]](#footnote-7) [(Schlicht-Schmälzle et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=12344151813767335&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:6a9141c6-6628-4444-8af4-2a3e13440629). Nevertheless, the authors calculated this test for an *unweighted* network, thus deviating from past research. Finally, another contribution stated that attitudes related to bio-products have a small-world structure [(Zwicker et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=04864875305296534&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:8c732dff-5588-4161-b313-520864427349). However, the authors mention this only in the theoretical part of their paper and avoid testing it empirically. Therefore, the alleged small-worldness of attitude networks needs to be tested again, even outside the domain of attitudes towards inequality. Cumulative research can help to understand whether these networks really conform to this structure, or are closer to a random network.

Also H2 was fully grounded in theory. When change occurs at central -rather than peripheral- nodes, the attitude network should vary to a greater extent, because evaluative reactions are part of a densely connected network in which influence flows rapidly [(Borsboom et al., 2021; Dalege, Borsboom, Harreveld, & Maas, 2017; Dalege, Borsboom, Harreveld, Waldorp, et al., 2017; Dalege et al., 2016, 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=5759076178390169&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:77902d13-3eed-470a-a4fc-1d0e839ca6bb,c61b91da-fa6e-4348-80b6-c2428280b16a:5b2491db-b30c-4f58-ab39-c2c7471d3c9c,c61b91da-fa6e-4348-80b6-c2428280b16a:7d183f8f-3926-411e-b1c5-4d2005fe8777,c61b91da-fa6e-4348-80b6-c2428280b16a:12564573-44ed-454b-a58b-80c7e2932eec,c61b91da-fa6e-4348-80b6-c2428280b16a:a2c9eb4c-32c5-4fe3-9d5b-27c5022c4699). This hypothesis was first tested in two simulation studies adopting the same research design proposed here [(Dalege, Borsboom, Harreveld, & Maas, 2017; Schlicht-Schmälzle et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9457120493866267&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:5b2491db-b30c-4f58-ab39-c2c7471d3c9c,c61b91da-fa6e-4348-80b6-c2428280b16a:6a9141c6-6628-4444-8af4-2a3e13440629). To ensure full cumulativity, we perform simulated manipulations of the same force (e.g.: same values of the thresholds). Our results are indicative of changes of moderate magnitude when compared to these simulations[[9]](#footnote-8). However, our research design is difficult to compare with those adopting panel data. For example, one contribution estimated the network of attitudes related to job satisfaction from data collected in 2006 [(Carter et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=19702633795798474&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:cbee107f-f476-44cf-ac6c-c76e7fb5ee99). In a second step, the authors regressed the most central nodes of that network on the overall index of job satisfaction estimated from data fielded in 2010. Although the results confirmed that central nodes are better predictors of future job satisfaction than peripheral ones, the research design employed in that study lacks the full control of external stimulus we can achieve with simulated data. Experimental research designs are more similar, in that the network estimation performed at Time 0 is followed by direct manipulation of central and peripheral nodes at Time 1 [(Chambon, Dalege, et al., 2022; Zwicker et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=6936827675261789&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:d318829d-ff0c-465e-bc63-02415fe27799,c61b91da-fa6e-4348-80b6-c2428280b16a:8c732dff-5588-4161-b313-520864427349). Then, at Time 2, participants are interviewed again to obtain a second network estimation. In both cases, the changes in attitude networks can be explained by the manipulations performed at Time 1. However, only one of these two works found evidence of proper downstream effects [(Chambon, Dalege, et al., 2022; Zwicker et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=470366123831494&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:d318829d-ff0c-465e-bc63-02415fe27799,c61b91da-fa6e-4348-80b6-c2428280b16a:8c732dff-5588-4161-b313-520864427349), whereas the other only found a strong change in the mean value of the targeted node [(Chambon, Dalege, et al., 2022; Zwicker et al., 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=874232136219129&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:d318829d-ff0c-465e-bc63-02415fe27799,c61b91da-fa6e-4348-80b6-c2428280b16a:8c732dff-5588-4161-b313-520864427349).

# Conclusions

This paper represents the first application of the CAN model to the multidimensional concept of attitudes towards inequality. Each dimension of this construct was measured through survey items addressing inequality, redistribution, and taxation. In this way, we respond to the call of distributive justice research to systematically address how people understand inequality [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=7331964329017844&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a). These variables formed a fully connected network, which means that all these topics are essential to validly study the concept in question. Contrary to our expectations, we did not find support of the small-world hypothesis. As pointed out in the discussion, this has major consequences for the literature on attitude networks. Importantly, network nodes clustered into two communities where variables strongly interact regardless of the dimension or the topic they were referring to. However, perception of income inequality and belief in public redistribution emerged as the most important nodes in the attitude network. Consistently, when targeted with simulated manipulation attempts, these items induced changes in neighboring nodes. Thus, our results support the hypothesis that changes in central -rather than peripheral- nodes lead to downstream effects in the CAN network. By avoiding the reduction of these evaluative reactions to indices -as is commonly done when working with latent variable models- we were able to provide the reader with a holistic comprehension of the relationships between the components of attitudes towards inequality in Italy.

This research has important limitations. First, the original variance of the selected items was reduced by the constraint imposed by the CAN model, which is limited to dichotomous variables. Therefore, we were forced to study associations between items that were endorsed or rejected. Alternative network models operating with full-scale variables are already available in the literature, such as the Gaussian Graphical Model [(Epskamp, Waldorp, et al., 2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=4537156486225081&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:186fe824-a832-409a-ba25-0d8aa0ee2418) and the Mixed Graphical Model [(Haslbeck & Waldorp, 2020)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=3513481579598803&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:633ef322-7aeb-4178-852a-5ee3fd70b73d). However, the selection of network models presents a trade-off, as both are unable to simulate attitudinal change, as CAN does. Yet, these techniques could be applied to mitigate the second limitation of this research, which is the use of simulated rather than panel or experimental data. We encourage future research to explore a wider set of variables related to attitudes towards inequality and study them longitudinally, to address variations in their internal structure.

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1. Department of Social and Political Sciences, University of Milan, Via Conservatorio, 7, 20122 Milan, Italy. <https://orcid.org/0000-0001-6014-1794> [↑](#footnote-ref-0)
2. Department of Social and Political Sciences, University of Milan, Via Conservatorio, 7, 20122 Milan, Italy. <https://orcid.org/0000-0003-0337-0739> [↑](#footnote-ref-1)
3. This is due to the influential Tripartite Model of attitudes, which infrastructures attitude research in social psychology (Dalege et al., 2016). In this account, an attitude can be decomposed - and thus measured - into three components. These insist on emotional responses (affective component), concrete actions (behavioral), and beliefs or thoughts (cognitive) provoked by the attitude object (Eagly & Chaiken 1993; Ajzen & Fishbein 1975; Rosenberg et al. 1960). However, to the best of our knowledge, the Tripartite Model has never been applied to attitudes towards inequality. Therefore, we rely on the abovementioned operationalization [(Janmaat, 2013)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=8245484007914838&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:a5fe0957-21b3-4f66-991b-a1b55320ca5a). [↑](#footnote-ref-2)
4. Recall that this perception is measured as the agreement with the statement: “income differences are too large”. Scholars argue that this sentence is problematic because of the word “too”, which implicitly ask also for a judgment about existing distribution of resources [(Castillo et al., 2022; Heiserman & Simpson, 2021)](https://app.readcube.com/library/0a3c846c-7570-4913-bd72-3afd46468081/all?uuid=9380853339916082&item_ids=0a3c846c-7570-4913-bd72-3afd46468081:9bd8c586-f281-4955-8f3c-6e51987088c3,0a3c846c-7570-4913-bd72-3afd46468081:a123e7af-25ea-45ba-a323-df8658e82f3f). [↑](#footnote-ref-3)
5. Small-world index of 0.836. [↑](#footnote-ref-4)
6. Small-world index of 1.16. [↑](#footnote-ref-5)
7. Small-world indexes ranging between 1.00 and 1.22. [↑](#footnote-ref-6)
8. Small-world index of 1.27. [↑](#footnote-ref-7)
9. In our simulation we found a baseline mean of -2.137, and the strongest manipulation resulted in a mean of 0.852. Dalege and colleagues [(2017)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=1665093857015182&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:5b2491db-b30c-4f58-ab39-c2c7471d3c9c&options=%7B%22items%22%3A%7B%22c61b91da-fa6e-4348-80b6-c2428280b16a%3A5b2491db-b30c-4f58-ab39-c2c7471d3c9c%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D) obtained a baseline mean of -5.63. The means of the manipulated networks ranged from -1.04 to 1.18. Similarly, Schlicht-Schmälzle, Chykina, and Schmälzle [(2018)](https://app.readcube.com/library/c61b91da-fa6e-4348-80b6-c2428280b16a/all?uuid=9173495267215717&item_ids=c61b91da-fa6e-4348-80b6-c2428280b16a:6a9141c6-6628-4444-8af4-2a3e13440629&options=%7B%22items%22%3A%7B%22c61b91da-fa6e-4348-80b6-c2428280b16a%3A6a9141c6-6628-4444-8af4-2a3e13440629%22%3A%7B%22suppressAuthor%22%3Atrue%7D%7D%7D) found a baseline mean of approximately -12; the highest mean of manipulated networks was around -6. [↑](#footnote-ref-8)