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# The role of social networks in institutional trust during economic downturns

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Citizens' trust in institutions is crucial for the proper functioning of societies. While national economic performance is a key predictor of institutional trust, individuals' perceptions of the economy—through which this influence is thought to operate— vary widely, suggesting that additional factors play a role in shaping these perceptions. One largely ignored factor is social networks. This paper argues that acquaintanceship networks expose individuals unevenly to the economic conditions of others, which in turns shapes their trust in institutions. Using Spain as a case study in the aftermath of the 2008–2014 financial crisis, the study examines how individuals' network exposure to economic distress relates to their institutional trust. Data from a nationally representative survey show that network homogeneity results in uneven exposure to the crisis's negative effects among individuals from different socioeconomic and age groups, potentially biasing their economic perceptions. Even when controlling for household income, employment status, education, age, and other variables, greater network exposure to distress remains significantly associated with lower institutional trust. These findings highlight the crucial role of social networks in institutional trust.

## Introduction

Institutional trust is a cornerstone of the effective functioning of democracies and economic growth (Hetherington, 1998; Hwang, 2017). It underpins the legitimacy of democratic government and the smooth operation of markets (Easton, 1965; Newton and Norris, 2000; Roth, 2009). Additionally, trust influences voting behaviour, as distrusting citizens are more inclined to support anti-incumbent and populist parties (Dalton and Weldon, 2005; Hooghe, 2017). Given its critical role in society, it is important to understand what influences institutional trust.

A country's economic performance is one of the most consistent macro-level predictors of citizens' institutional trust (Van der Meer, 2017). Individuals perceive the national economy as a relevant indicator of political success, leading them to place more trust in responsible institutions when the economy is performing well (Van der Meer, 2017). While, on average, individuals' perceptions of the economy reflect economic reality (Duch and Stevenson, 2010), these perceptions vary widely within the same country at the same time (Duch, Palmer, and Anderson, 2000). This variation suggests that other (micro- or meso-level) variables influence how citizens perceive the economy. These variables include individual ones such as income, age, gender, education, and political orientation, which significantly influence individuals' institutional trust (e.g. Kaasa and Andriani, 2022).

One meso-level variable that has hardly received attention in research on institutional trust is individuals' networks of social relationships. Yet, studies suggest that individuals often form their views on the economy (e.g. of inequality) and society (e.g. political leaders) based on information they receive about other people's wellbeing from their social networks (Mondak *et al.*, 1996; Galesic, Olsson, and Rieskamp, 2012; Ansolabehere, Meredith, and Snowberg, 2014; Newman, 2014; Mijs, 2018). Social networks play a crucial role in disseminating information (Centola, 2018) and can amplify experiences of economic hardship, even among those not personally affected. However, these networks often consist of people with similar socioeconomic backgrounds (Chetty *et al.*, 2022; Kazmina, Heemskerk, Bokanyi, 2024), meaning individuals are more likely to hear about the experiences of people in similar economic situations as their own. This network homogeneity might cause interindividual variation in perceptions of the economy, polarising institutional trust. If network exposure to economic

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distress influences institutional trust, it would call for new approaches to strengthen trust in institutions, addressing social segregation.

To study whether social networks play a role in institutional trust, this paper examines how, in Spain during the 2008–2014 financial crisis, individuals' network exposure to economic distress is associated with their institutional trust. Spain is a relevant context because the crisis hit Spain hard. Unemployment and eviction rates tripled, poverty rose, and the country experienced negative net migration for the first time since 1990 (see below). Severe economic crises tend to erode public confidence in both political and impartial institutions (Roth, 2009; Ervasti, Kouvo, and Venetoklis, 2019), which was also observed in Spain (Torcal, 2014; Eurofound, 2018). While this decline is typically attributed to citizens' personal economic hardship and negative evaluations of political responsiveness (Torcal, 2014), I argue that exposure to the economic difficulties of family, friends, and acquaintances also lowers institutional trust. Therefore, this paper aims to assess (i) to what extent individuals' social networks were evenly exposed to economic distress at the end of the crisis, and (ii) whether higher network exposure to economic distress is associated with lower institutional trust, controlling for individuals' own socioeconomic attributes and regional economic performance to avoid omitted variable bias.

The paper makes three core contributions to the literature. First, it examines the sparsely studied relationship between social networks and institutional trust. Specifically, while research that associates networks with related concepts, such as evaluations of presidential candidates (Mondak *et al.*, 1996) or support for welfare policies (Newman and Vickrey, 2017), often focuses on core networks or specific social settings, this study argues that broader acquaintanceship networks are more relevant sources of information for forming institutional trust, drawing on network theory and cognitive sociology. Therefore, this study analyzes the relationship between acquaintanceship networks and institutional trust and compares core and acquaintanceship networks.

Second, by focussing on a period where economic hardship sharply increased in little time, I aim to mitigate concerns about reverse causality. While the cross-sectional design precludes establishing definitive causal claims, asking respondents to report the number of people they knew who experienced specific types of economic distress over the past three years and relating it to their current trust, as well as the sharp rise in average network exposure to distress as a direct consequence of the crisis suggest a directional influence from exposure to economic distress to trust.

Third, this study contributes to research on acquaintanceship networks by adopting a promising approach to assess their homogeneity, as proposed and implemented by Zheng, Salganik, and Gelman, (2006) and DiPrete and colleagues (2011) in the US. It collects aggregated relational data, which are responses to survey questions of the form 'how many people do you know [in subpopulation X]?' for a series of subpopulations. When combined with national statistics on the size of (part of) these subpopulations, these data can be used to estimate acquaintanceship network size via the Network Scale-Up Method (NSUM; Bernard, Johnsen, Killworth 1989; McCormick, Salganik, and Zheng, 2010) and network homogeneity (Zheng, Salganik, and Gelman, 2006), although this latter application is less common. This paper adopts this approach in another empirical setting (cf. Lubbers, Molina, and Valenzuela-García, 2019) to investigate how acquaintanceship networks in Spain vary in their exposure to economic distress across social groups. It provides new insights into the use of aggregated relational data for understanding acquaintanceship networks.

The paper is structured as follows. It first introduces the concept of acquaintanceship networks and the sources of their homogeneity. It then defines institutional trust and articulates the theorised mechanism linking social networks to institutional trust. Next, it describes the study context and derives hypotheses. Finally, the paper presents the methods, results, conclusions, and implications.

## Social network homogeneity

*'Acquaintanceship networks'* are individuals' sets of interpersonal relationships with the people they mutually know by sight and by name (cf. DiPrete *et al.*, 2011) across all social settings in which they participate (e.g. family, work, school, neighbourhood, places of worship, clubs). These networks are conceptualised as layered (Kahn and Antonucci, 1980; Dunbar, 2014), with a core of a few intimate, supportive, and enduring (or 'strong') ties –often partners, best friends, and first-degree relatives– and a periphery of hundreds of superficial or 'weak' ties (Granovetter, 1973; Blau, 1974; Putnam, 2000). The large number of relationships makes acquaintanceship networks a key ingredient of human sociality, providing individuals with a sense of belonging, positive affect, and support (Sprecher, 2022). They also expose individuals to a great number and diversity of people, extending beyond intimate circles and establishing inter-group connections (Granovetter, 1973; Blau, 1974). Acquaintanceship networks are, therefore, a potent source of information about society.

Although acquaintanceship networks are assumed to be more diverse than core networks, they also exhibit homogenising tendencies (McPherson, Smith-Lovin, and Cook, 2001) that make them deviate from '*random mixing*'. Random mixing occurs when the likelihood of social relationships within and across social groups is based solely on the relative sizes of those groups and individuals' network sizes (Bernard *et al.*, 1989). Deviation from random mixing has several reasons. First, social and institutional settings, such as neighbourhoods and workplaces, tend to attract people with similar attributes, like income or race, thereby increasing their interaction opportunities (Blau, 1974). Exceptionally, voluntary associations may attract *more* diverse memberships and are, therefore, often praised for their integrative function in society (Putnam, 2000). A second homogenising tendency is '*homophily*', the preference for contact with people who are similar in age, class, or other attributes to oneself, and its counterpart '*heterophobia*' (Wimmer and Lewis, 2010), the reluctance to engage with dissimilar people. These preferences arise because people with shared backgrounds communicate more easily. A related phenomenon is '*secondary homophily*', which refers to homogeneity in one attribute (e.g. income) resulting from preferences for similarity in a correlated attribute (e.g. age; Shalizi and Thomas, 2011). While the first reason –opportunity structures– increases the homogeneity of both strong and weak ties in acquaintanceship networks, the second –homophily– is presumably more pronounced in strong ties. These and other mechanisms (Wimmer and Lewis, 2010) cause social networks to be more homogeneous than random mixing would predict (McPherson *et al.*, 2001; Thomas, 2019).

Empirical tests widely confirm the homogeneity of both core (McPherson *et al.*, 2001; Thomas, 2019) and broader networks (e.g. Chetty *et al.*, 2022; Kazmina *et al.*, 2024). Studies on broader networks often use behavioral trace data to reconstruct networks, which, while valuable, do not capture cognitive variables such as trust. For such variables, researchers usually need surveys. A survey instrument to assess acquaintanceship network size and homogeneity is the Network Scale-Up Method and its extensions (e.g. Bernard *et al.*, 1989; Killworth, Johnsen, Bernard, 1990; Zheng *et al.*, 2006; DiPrete *et al.*, 2011). Using these methods with data from the 2006 US General Social Survey, DiPrete *et al.* (2011) surprisingly observed similarly strong homogeneity in Americans' perceived acquaintanceship networks as in their core networks regarding race, employment status, religiosity, and political orientation. Network homogeneity has implications for the information individuals acquire from their networks about society and can be expected to influence their institutional trust, as I will now discuss.

## Social network homogeneity and institutional trust

Institutional trust refers to individuals' evaluations of 'the expected utility of institutions performing satisfactorily' (Mishler and Rose, 2001: p. 31). It is a cognitive judgment (Levi and Stoker, 2000; Hardin, 2002) regarding how well institutions fulfil their role. It is typically conceptualised and measured as an aggregate of trust in various institutions. In financial crises, people tend to lose confidence not only in the government but also in other institutions perceived as unresponsive to public needs (Torcal, 2014; Ervasti *et al.*, 2019). For instance, in Spain, churches were involved in charitable redistribution, banks played decisive roles in evictions, and judicial and police authorities enforced those evictions during the crisis. Measuring trust as a composite variable across institutions is, therefore, appropriate.

Research has identified two sets of predictors of institutional trust: individual attributes, such as personality, income, and gender (Ward, Miller, Pearce, 2016; Citrin and Stoker, 2018), and macro-level factors (Mishler and Rose, 2001), particularly macro-economic performance (Van der Meer, 2017). Macro-level performance is thought to shape citizens' trust through their subjective evaluations of that performance. While citizens' perceptions of the economy, on average, align with economic reality (Duch and Stevenson, 2010), they vary significantly among individuals in the same country and at the same time (Duch *et al.*, 2000), suggesting that micro- or meso-level variables play a role in the evaluative process. This paper explores whether acquaintanceship networks play a role in institutional trust.

Drawing on cognitive sociology, I argue that network exposure to economic conditions influences institutional trust. Cognitive sociology posits that individuals' perceptions of society and evaluations of institutions are socially situated, not formed in isolation (Rydgren, 2007; Mijs, 2018). For instance, Mondak, Mutz, and Huckfeldt (1996) argued that people's evaluations of the economy are shaped not only by their own financial situations and national economic performance but also by the economic experiences of their social circles:

> 'in between an individual's immediate life space and his or her perceptions of national conditions is a broad middle ground consisting of perceptions of successively larger collectives with whom people may interact' (p. 250).

These social circles have a 'vividness and immediacy' (p. 253) that makes them highly relevant sources of information about societal functioning (cf. Rydgren, 2007).

Likewise, Mijs (2018) argued that people do not necessarily learn about complex societal tendencies from 'what they are explicitly taught or told' (p. 64) –for instance, by newspapers–, but make inductive inferences about society by observing the people they encounter in the multiple social settings they participate in, such as neighbourhoods, workplaces, and schools. Galesic, Olsson, and Rieskamp (2012) similarly expected that people extrapolate properties of the population (e.g. income distributions) from the samples of the population available to them, including 'family, friends, and acquaintances they meet on a regular basis' (p. 1517). This inference process is referred to as *social inference* (Mijs, 2018) or *social sampling* (Galesic, Olsson, and Rieskamp, 2012).

As discussed earlier, network theory suggests that acquaintanceship networks expose individuals to a wide range of life experiences. Individuals learn about their acquaintances' lives through conversations and observation (e.g. neighbours at home during their usual working hours) and contextualise this experiential knowledge with information from other sources. They may use this knowledge to make social inferences about the economy.

Relatively homogenous acquaintanceship networks (see previous section) would bias the knowledge individuals obtain via social inference (Galesic *et al.*, 2012; Mijs, 2018), causing variation in how people perceive, for instance, economic hardship in society and institutions' effectiveness to remediate it. For example, a hypothetical corporate lawyer from a high-class family might observe fewer of the pernicious personal consequences of a financial crisis in her network across many social settings (e.g. family, her wealthy neighbourhood, her law firm and clients, friends from university, friends' friends, fellow members of her tennis club, fellow parents at her children's private school) than blue-collar workers, or than affluent people who know economically distressed individuals through their professions or upward mobility. Research has shown that individuals' perceptions of inequality and income distributions deviate from actual inequality and income distributions in ways compatible with this assumption (e.g. Mondak *et al.*, 1996; Knell and Stix, 2020; Londoño-Vélez, 2022). Extrapolating from these sources, I argue that social inference in networks characterised by a certain homogeneity causes variation in institutional trust in the same macro-level context, even when controlling for personal socioeconomic status.

## This study

This study is based on a survey conducted in Spain at the end of the 2008–2014 financial crisis. The crisis severely affected Spain, with unemployment rates rising sharply to 24.5 per cent of the active population and 53.2 per cent of the active youth in 2014, compared to 8.2 per cent and 18.1 per cent, respectively, in 2007 (Eurostat, n.d.-a, n.d.-b). In response, the government promoted self-employment as an alternative to wage labour, with mixed success (Cavas Martínez, 2016). Although Spain had been an immigration country for twenty years, many highly-educated young people sought jobs abroad, especially in Germany and the UK, resulting in negative net migration from 2010–2015 (González-Ferrer and Moreno-Fuentes, 2017). According to Spain's national statistics, more than 80.000 people with Spanish nationality emigrated in 2014 (a severe underestimation compared to statistics of several incoming countries), as opposed to less than 30.000 annually before the crisis (González-Ferrer and Moreno-Fuentes, 2017; Romero Valiente, 2018). The country's low welfare-state provision led to increased poverty (Lubbers *et al.*, 2020), and approximately 380.000 families, or nearly a million individuals, were evicted from their homes during the crisis (Observatori de Drets Económics, Socials i Culturals, 2020). Annual eviction rates were three (2008) to four times (2009–2014) higher than before the crisis (Méndez Gutiérrez Del Valle and Plaza Tabasco, 2016). Many, especially young people, were forced to return to their parental homes (Arundel and Lennartz, 2017). Average institutional trust decreased, while variation in institutional trust increased over time (Eurofound, 2018).

My first research question (RQ1) is: To what extent are individuals' social networks evenly exposed to economic distress at the end of the crisis? Based on the above, I identified six types of economic distress relevant in the Spanish context during the crisis (Arundel and Lennartz, 2017; González-Ferrer and Moreno-Fuentes, 2017; Lubbers *et al.*, 2020): unemployment following job loss, unemployment while seeking a first job (youth unemployment), eviction, forced return to the home of parents or other relatives, labour emigration, and self-employment. The latter two coping strategies were more viable for the higher educated (see above). I also explore three positive events potentially counterbalancing the perception of adverse events: finding jobs, starting to live independently from parents, and second-home ownership.

Based on network theories (see above), I hypothesise that *(H1) with equal network size, individuals with lower socioeconomic status (SES) and age have higher relative network exposure to economically distressed groups,* with some exceptions. SES was captured with employment status, education, and income, reflecting individuals' resilience during the crisis. Specifically, assuming that meeting opportunities and preferences produce network homogeneity in SES (McPherson *et al.*, 2001), I expect that (H1a) the *unemployed* know relatively more people in all six distressed groups than people with other occupational statuses, controlled for network size, as the unemployed were more vulnerable to economic distress. Similarly, I hypothesise that individuals with *lower education* (H1b) and *income* (H1c) know more people who had become unemployed, were unemployed looking for their first jobs, were evicted, or had to return to their parental homes, as lower-educated and lower-income groups were more vulnerable to these events. In contrast, individuals with higher SES may employ more diverse coping strategies when facing unemployment, including emigration (which tended to be 'skilled') and self-employment in the spatiotemporal context. Therefore, again assuming homophily in SES, I expect *highly educated* (H1d) and *high-income* (H1e) individuals to know more people who migrated for work or became self-employed. Finally, I focus on *age* as youth unemployment skyrocketed (see above). Assuming network homophily in age (McPherson *et al.*, 2001) and age's correlation with economic distress (i.e. *secondary homophily*), I expect that (H1f) younger people have more acquaintances in all distressed groups than older people.

My second research question (RQ2) is: Is higher network exposure to economic distress at the end of the crisis associated with lower institutional trust? Based on the theoretical mechanism of social inference from networks (i.e. network exposure to distress informs about macro-economic performance), I hypothesise that *(H2) independent of individuals' employment status, education, income, age, network size, and regional economic performance, higher network exposure to economically distressed groups is associated with lower institutional trust*. The control for individual attributes and regional differences in economic performance ensures that observed associations between networks and trust are not spurious results of their correlations with these attributes (i.e. omitted variable bias).

## Methods

### Sample and procedures

Data were collected in a special module we designed for the National Barometer, a survey conducted by the Spanish Center for Sociological Research (CIS)[1]. The study employed a multi-stage stratified sample of Spain's adult population with Spanish nationality. Primary (8,132 municipalities) and secondary sampling units (census tracts with up to 2,500 residents) were randomly selected with proportionate allocation. Tertiary units (individuals) were selected by random routing with sex and age quotas until the intended sample size was reached[1]. 2,468 individuals from 239 municipalities spanning all 52 provinces participated in the survey (51.3 per cent women; age $M = 48{,}2$; $SD = 17.2$).

Computer-assisted personal interviews were held in respondents' homes from December 11, 2014, to January 20, 2015. For this paper, I excluded respondents whom interviewers considered insincere or little sincere ($N = 53$), had inconsistent response patterns on the NSUM instrument[2] (additional $N = 115$), or missing values on estimated network size, SES (except income; see below), or control variables (additional $N = 22$). Therefore, this paper is based on 2,278 respondents (51.5 per cent women; $M_{age} = 47.6$, $SD = 17.1$). Missing values were excluded variable-wise for dependent and listwise for explanatory variables from this selection.

### Measures

#### *Acquaintanceship network size*

The known-population method for NSUM was used to estimate network size (Bernard *et al.*, 1989; Killworth *et al.*, 1990). The survey instrument (Lubbers *et al.*, 2019) asks respondents how many people they know in certain subpopulations, defining 'knowing' to survey respondents as

> 'you know this person by name, and you would stop and talk to this person if you'd see him or her on the street, in a shop, or wherever. This includes proximal relations such as your partner, family members, friends, neighbors, and work or study mates but also people you don't know so well.'

Respondents were told acquaintances do not need to live close. For estimating network size, McCormick *et al.* (2010) suggested using carefully selected, relatively rare first names as subpopulations (0.1–0.2 per cent prevalence), because names are well-known attributes of acquaintances, their low prevalence avoids memory bias, and names can be chosen from name statistics to jointly reflect society's gender and birth cohort composition (here, for the population of 15 years and older). Therefore, respondents were asked, for each of 14 carefully selected names (Lubbers *et al.*, 2019),

> 'How many people of 15 years or older do you know whose name is […]?'

Responses over 10 were combined in a single category. Based on the survey responses and national name statistics, individuals' acquaintanceship network size was estimated using the R-package NSUM (Maltiel *et al.*, 2015). People reporting not knowing anyone with these names had unrealistically small estimated network sizes of 1, which was recoded to the lower boundary of 110. The estimated median acquaintanceship network size was 527, with an interquartile range of 325–819 ($M = 651$; $SD = 487$). For the analyses, this right-skewed variable was log-transformed and centred. Recall bias and overdispersion were negligible (Lubbers *et al.*, 2019; Table S1 in the supplementary materials), showing that people mixed randomly concerning these names. Thus, no social class or other bias was identified.

### *Acquaintanceship network exposure to economic distress*

Respondents reported how many people over 15 years they knew in eleven relevant subpopulations (this paper uses nine), after they were reminded of the definition of knowing someone. Examples are people evicted in the past three years and second-homeowners (see Table 1 for the subpopulations, Figure S2 for distributions, Table S4 for zero-order correlations). Again, responses ranged from 0 to 10 with unit increases, plus the right-censored category 'more than 10' (11).

For RQ1, each subpopulation was analysed separately. For RQ2, a factor analysis on the Spearman correlations between these counts reduced the number of variables in the analysis (see Table S5). Two underlying factors emerged: exposure to economic distress (unemployment, evictions, return to the parental home, migration) and to economic wellbeing (acquaintances finding jobs, becoming selfemployed, owning second homes, leaving the parental home). The number of acquaintances looking for first jobs loaded similarly on both factors in the non-parametric analysis and was therefore excluded. I averaged the valid responses of the four variables per factor ($M_{distress} = 2.57$; $Me = 2.25$; $SD = 1.92$; $M_{wellbeing} = 1.78$; $Me = 1.25$; $SD = 1.66$) and median-centred them.

### *Core network size and exposure to economic distress*

For comparison and control, respondents also reported how many friends and how many relatives older than 15 years they had in the subpopulations, using the same response format as before (see Figure S3, Table S4). They further estimated their total number of friends ($M_{friends} = 5.8$, $SD = 5.8$) and relatives ($M_{relatives} = 16.9$; $SD = 12.6$), which were summed for core network size, and log-transformed and centred for generalised linear modelling.

### *Institutional trust*

Institutional trust was assessed using a widely employed instrument (Montero, Zmerli, and Newton, 2008), asking respondents how much they trust a series of institutions on a 10-point scale. In this case, institutions were the central government, police, political parties, judicial authorities, trade unions, private enterprises, churches, and banks. This instrument preceded survey questions about networks in the questionnaire. Factor analysis with Varimax rotation (Table S6) confirmed that all but one item (unions) loaded > 0.4 on a single dimension. I averaged the valid responses on the remaining seven ($M = 3.36$; $SD = 1.81$; $N = 2{,}261$; Cronbach's $\alpha = 0.83$). The conclusions were similar when up to two missing values were allowed (see Table S18). Outliers 1.5 IQR above the third quartile were censored to that threshold.

### *Socioeconomic status*

Socioeconomic status was measured with three variables: The highest educational degree completed was recoded into (i) no/primary education, (ii) 1st stage secondary or basic professional education (mode and reference category), (iii) 2nd stage secondary and middle professional; (iv) post-secondary professional, (v) university education. Occupational status was recoded to (i) inactive (including retirees, pensioners, and unpaid domestic workers), (ii) unemployed, (iii) (self-)employed (reference category), (iv) student. Net monthly household income (11 categories ranging from 'no income of any kind' to 'more than €6,000') was equivalized by household composition[3], producing five categories, (i) below or around the extreme poverty threshold (i.e. 40 per cent of Spain's median income), (ii) below the poverty threshold (60 per cent of the median income), (iii) between the poverty threshold and median income, (iv) approximately median income (reference category); (v) above the median income. Missing values were retained as a separate category (vi) as non-response was high ($N = 688$), and missing income is often non-random. The other variables had a few missing cases, which were excluded (see above). *Age* in years was standardised for the effective sample.

### *Individual control variables*

*Gender* was coded as binary. *Associational membership* was measured by counting the types of associations respondents actively participated in, among nine: political party, trade union/entrepreneurs' association, professional college, religious organisation/association, sports club, cultural/leisure group, social/human rights organisation, youth/student association, others. Dummy variables distinguished between membership in (i) one and (ii) multiple types of associations versus none (reference category). *Political orientation,* a consistent predictor of institutional trust (used for RQ2), was measured on an 11-point left-right scale and median-centred. Outliers 1.5 IQR above the third quartile were recoded to that cut-off value.

### *Regional economic performance*

Regional economic performance was measured by the province's GDP per capita (cf. Kaasa and Andriani,

**Table 1** Descriptive statistics of the location and dispersion of the number of acquaintances, relatives, and friends in subpopulations

| HOW MANY PEOPLE OVER 15 YEARS OLD DO YOU KNOW WHO... | Me | EXTENDED *NETWORK* | | | | | FAMILY | | Me | | FRIENDS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | IQR | per cent who know 0 person in subpop. | per cent who know ≥ 5 persons in sub-pop. | Me | IQR | per cent who have 0 relatives in subpop. | per cent who know ≥ 5 persons | | IQR | per cent who have 0 friends in subpop. | per cent who know ≥ 5 persons in subpop | per cent of those with 0 family and 0 friends in subpop. | per cent with family/friends in sub-pop. who have ≥ 1 acquaintance(s) |
| ... have lost their job in the last 3 years? | 6 | 3–11 | 7.8 | 62.4 | 1 | 0–3 | 28.2 | 13.5 | 1 | 0–3 | 45.1 | 14.1 | 18.0 | 58.5 |
| ... are young people looking for their first job? | 2 | 0–5 | 31.5 | 29.9 | 0 | 0–1 | 57.3 | 5.6 | 0 | 0–0 | 78.7 | 5.8 | 49.3 | 38.7 |
| ... have found a job in the last 3 years? | 2 | 1–4 | 22.1 | 17.2 | 1 | 0–1 | 49.3 | 1.3 | 0 | 0–1 | 61.6 | 1.9 | 33.7 | 39.2 |
| ... became self-employed in the last 3 years? | 0 | 0–1 | 54.0 | 2.9 | 0 | 0–0 | 79.4 | 0.1 | 0 | 0–0 | 85.2 | 0.2 | 70.7 | 24.1 |
| ... have migrated to work or search for work in the last 3 years? | 1 | 0–2 | 41.5 | 12.0 | 0 | 0–0 | 78.5 | 0.5 | 0 | 0–0 | 79.2 | 2.4 | 65.2 | 36.9 |
| ... were evicted in the last 3 years? | 0 | 0–0 | 81.6 | 3.0 | 0 | 0–0 | 95.6 | 0.1 | 0 | 0–0 | 94.5 | 0.4 | 91.5 | 11.1 |
| ... are second-home owners? | 1 | 0–3 | 41.5 | 19.5 | 0 | 0–1 | 63.3 | 5.0 | 0 | 0–0 | 75.5 | 3.1 | 53.6 | 25.7 |
| ... had to return to parental home or other relatives in the last 3 years? | 1 | 0–2 | 43.7 | 11.8 | 0 | 0–1 | 72.2 | 0.9 | 0 | 0–0 | 77.2 | 1.4 | 61.4 | 29.8 |
| ... are young people who left the parental home in the last 3 years? | 0 | 0–2 | 53.4 | 7.2 | 0 | 0–1 | 75.0 | 0.7 | 0 | 0–0 | 86.9 | 1.0 | 67.6 | 22.5 |

*Note*: Me = Median; IQR = interquartile range; subpop. = subpopulation. Missing values were case-wise excluded; percentages taken from valid cases only.

**Table 2** Analysis of institutional trust using GLMM for lognormally distributed variables ($n$ = 1,629)

| PARAMETERS | PARSIMONIOUS MODEL | | |
|---|---|---|---|
| | B | 95 per cent CI | |
| | | Lower | Upper |
| Intercept | 3.244*** | 3.109 | 3.384 |
| Age (Standardized[a]) | 1.060*** | 1.035 | 1.085 |
| Political orientation (Left-right, median-centered[a]) | 1.079*** | 1.066 | 1.093 |
| Associations (Ref.: No) | | | |
| 1 type | 1.054*** | 0.997 | 1.114 |
| 2 or more types | 1.167*** | 1.087 | 1.254 |
| Network size (ln, centered[a]) | 1.073*** | 1.031 | 1.117 |
| Network exposure (median-centered) to… | | | |
| Economic wellbeing | 1.051*** | 1.035 | 1.067 |
| Economic distress | 0.937*** | 0.924 | 0.952 |
| Variance individual level | 2.443*** | 2.278 | 2.620 |
| Variance group level | 0.008* | 0.004 | 0.019 |
| Conditional ICC | | 0.030 | |
| AIC corrected | 2,316.6 | | |
| Conditional Pseudo R2 | 0.212 | | |

*Note:* [a]For these analyses, values 1.5 IQR above the third quartiles were censored to that threshold.
*$p$ < 0.05; **$p$ < 0.01; ***$p$ < 0.001 (two-tailed tests).

2022; data from the Instituto Nacional de Estadística, 2023a). In separate analyses (to avoid multicollinearity), I used the unemployment rate (last trimester 2014), migration rate (last semester 2014), and relative evictions in 2014 (Instituto Nacional de Estadística, 2023b, 2023c, 2023d) for selected exposure variables. Relative evictions were calculated by dividing the number of homes with started foreclosures by the province's population size. Due to non-normal distributions, I categorised each variable into three terciles at the province level (the first tercile is the reference category). Table S7 presents descriptive statistics of the explanatory variables.

## Analyses

Generalized linear mixed models (GLMM) were used to account for the hierarchical data structure resulting from the multi-stage sampling procedure, as ignoring this nesting could underestimate standard errors (e.g. Snijders and Bosker, 2011). Individuals were nested within the primary sampling units, provinces ($N$ = 52)[4]. The multilevel models also account for regional variations in macro-economic performance, which should affect the numbers of people known in different economic situations as most acquaintances are local people.

For RQ1, I separately modelled individuals' total number of acquaintances and the sum of friends and relatives in each subpopulation. For their highly right-skewed and censored distributions (see Figures S2-S3), I recoded the exposure variables into four categories (0; 1–3; 4–9; 10–11) or exceptionally, when the number of acquaintances in the upper category was low, three categories (0, 1–3, 4–11), and used ordered multinomial GLMMs. I specified random-intercept models with SES, age, estimated extended network size (for acquaintances) or core network size (for family and friends), and control variables as predictors. For low frequencies of the upper categories of friends and relatives, I conducted robustness analyses with fewer categories (3 and 2, respectively), with highly similar results (see Table S14).

To model institutional trust (RQ2), I used GLMM for lognormal distributed variables (log link function) for its right-skewed distribution. After fitting an empty random-intercept model, I added network exposure (Model 1), the interaction between the two exposure variables (Model 2), tested respondents' attributes and GDP as the sole predictors (Model 3), and then combined all predictors (Model 4). Finally, I tested a parsimonious model (Model 5), including only effects significant at $p$ < 0.01 in Model 4. Table 2 presents this model (see Table S16 for stepwise modelling). Tables S17-S19 and Figure S20 show additional and robustness analyses.

## Results

### Descriptive statistics of network exposure

Among friends and family, most respondents perceived minimal economic distress in the form of youth unemployment, eviction, return to the parental home, or emigration, with medians of zero friends and relatives for most subpopulations, except unemployment (see Table 1, Figure S2). *Acquaintanceship networks* showed higher absolute exposure: Respondents reported a median of six acquaintances who had lost their jobs in the past three years, reflecting Spain's high unemployment. They also reported medians of two unemployed youths, two acquaintances who had found jobs, one who had migrated for work, one who returned to their parents'/relatives' home, and one second-home owner. In contrast, most respondents (82 per cent) were unaware of acquaintances having been evicted, becoming self-employed (54 per cent), or independent of their parents (53 per cent).

Acquaintanceship network exposure varied considerably (see Table 1). For instance, 62 per cent of respondents knew at least five people who had become unemployed, but some reported not knowing anyone. In subpopulations with medians of zero, a minority (3–7 per cent) had at least five acquaintances, suggesting uneven absolute exposure to economic distress.

Reported exposure was lower than actual exposure. First, respondents' number of friends and relatives in a subpopulation is about half the total number of people they knew in that subpopulation, suggesting that respondents thought beyond their core networks when asked about acquaintances but did not consider everyone they knew (estimated median network size 526.5). Second, the average number of acquaintances in all subpopulations was lower than could be expected based on national statistics, assuming random mixing. For instance, given estimated network sizes and official eviction statistics, one could logically expect that individuals know, on average, approximately 2.5 evicted people (assuming random mixing and after rounding and right-censoring to make the expected data comparable to observed data). The observed average, however, was 0.5. This discrepancy suggests '*transmission error*', where individuals lack knowledge of their acquaintances' eviction. Consequently, individuals' acquaintanceship networks are larger than the number of people whose attributes respondents can assess. Therefore, responses were interpreted as *perceived* rather than actual exposure, which is still expected to shape individuals' views on society (cf. Thomas theorem). Furthermore, this was why I did not analyse residuals like DiPrete *et al.* (2011), the discrepancies between observed and expected values under random mixing. Instead, assuming the number of people about whom respondents make assessments correlates with their acquaintanceship network size (Brewer, 2000), I analysed the exposure variables directly, controlling for network size (McCormick *et al.*, 2013; see Methods).

### H1: Uneven network exposure to economic distress across social groups

To test H1, I analysed whether SES and age predicted perceived network exposure. All zero-order correlations between the SES variables and age, on the one hand, and the exposure variables, on the other, were significant for both acquaintances and core networks (see Tables S8-S11).

Using GLMMs, I then controlled for network size and other relevant variables (see Figure 1, visualising Tables S12–S13). Networks showed homogenising tendencies in SES. First, regarding (H1a), *unemployed* respondents knew significantly more people who had lost their jobs or returned to the parental home than employed respondents, but did not differ significantly in other distress groups. Students knew considerably more people seeking their first jobs than employed respondents but were significantly less exposed to other forms of economic distress (return to the parental home, job loss, and evictions) and self-employment.

Second, regarding education, *university graduates* reported having significantly fewer evicted acquaintances (H1b) and more acquaintances experiencing economic wellbeing (finding work, leaving the parental home, and second homeownership) than lower-educated respondents. Contrasting H1b, they did not differ in network exposure to job loss, youth unemployment, and return to the parental home. Supporting H1d, they observed more coping strategies in their networks (migration, self-employment).

Third, regarding income, individuals in poor households knew significantly more people experiencing job loss and eviction than those with median *household income* (H1c), and fewer people who found jobs. However, they did not differ in exposure to youth unemployment and return to the parental home. Contrary to H1e, people in poor households knew *more*, not *fewer*, people who had migrated for work but did not differ in exposure to self-employment.

For *age* (H1f), younger respondents knew significantly more people than older respondents across all distress subpopulations (supporting H1f). Notably, they also had more acquaintances who found jobs and became independent of their parents, controlled for network size. In contrast, they knew fewer second-home owners. Thus, Spanish youth's high labour and residential mobility also characterise their network members.

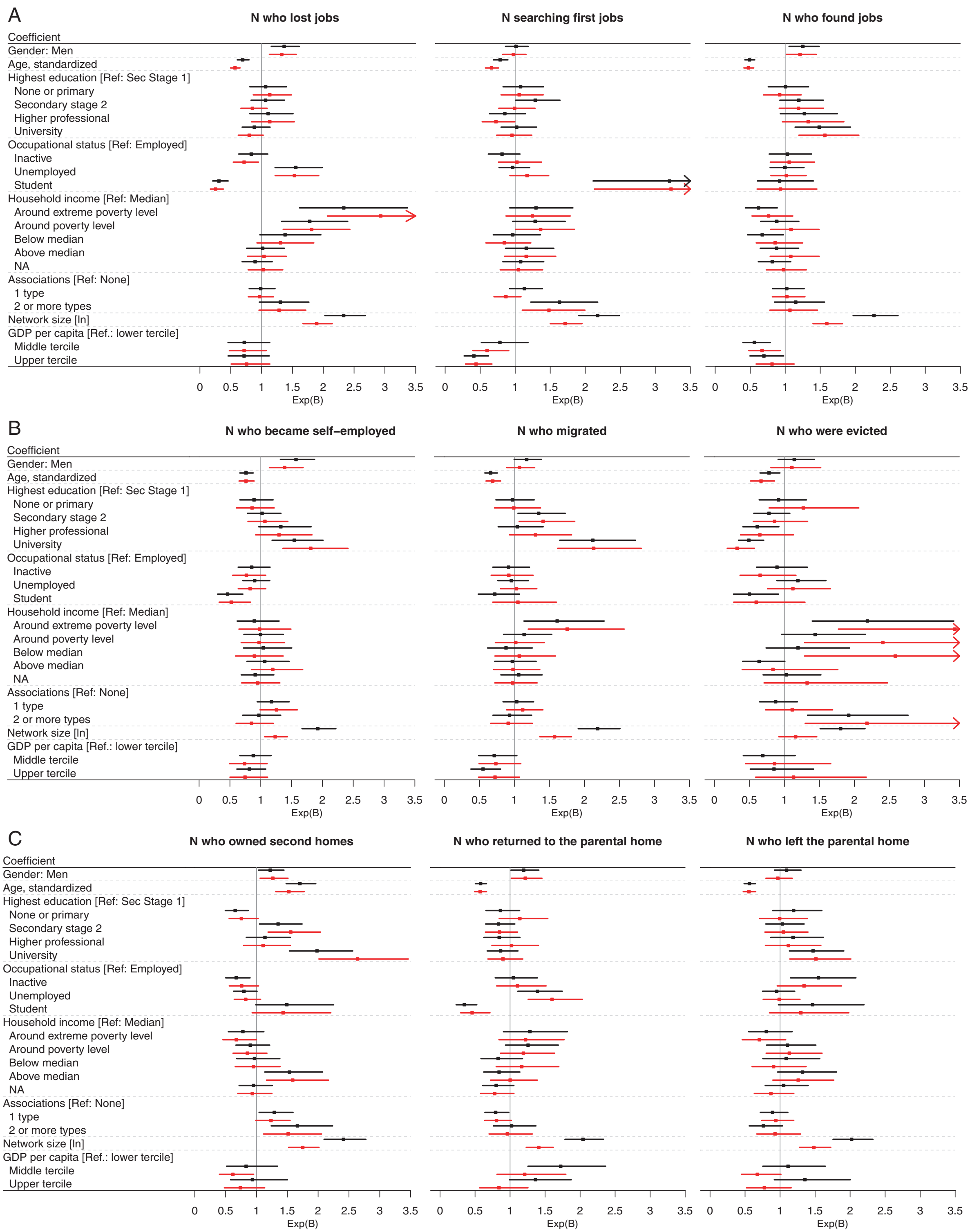


**Figure 1** Forest plots of multilevel regression of the total number of acquaintances and of friends and relatives in each subpopulation

*Note:* Respondents' number of acquaintances (▬) and the sum of their number of friends and family (▬) in each subpopulation were analysed separately. Network size was acquaintanceship network size (for acquaintances) or core network size (for family and friends). Dots represent Exp(*B*) estimates; lines 95 per cent confidence intervals (sometimes clipped, indicated by arrowheads). See Supplementary Materials (S12/S13).

Regarding the control variables, men were more exposed to job loss and self-employment through their networks than women. *Active participation in multiple types of voluntary associations* was related to higher network exposure to both economic hardships (youth unemployment, eviction) and favourable conditions (second-home ownership), controlled for other attributes. This finding supports the view that especially multiple memberships create social capital (Glanville, 2016). As expected, *network size* positively predicted exposure to all groups.

*Provincial GDP per capita* was related to network exposure to youth unemployment, job finding, labour emigration, and returning to the parental home. Substituting GDP with provincial characteristics more closely related to some exposure variables (e.g. eviction rate for exposure to evictions; Table S15) revealed that provincial unemployment rates were related to the number of acquaintances who lost jobs, found jobs, and were seeking their first jobs. Provincial eviction rates were related to the number of evicted acquaintances. These findings suggest that reported network exposure is anchored in economic realities, supporting the validity of network responses. However, provincial emigration rates were unrelated to network exposure to labour migration.

SES, age, and control variables were similarly related to perceived network exposure in core and acquaintanceship networks (see Figure 1). This finding echoes DiPrete et al's (2011) findings but contrasts classical macro-sociological assumptions of the larger heterogeneity of acquaintanceship networks. Core networks had larger confidence intervals. Despite clearly significant effects, the model fit shows substantial unexplained variance.

## H2: Perceived network exposure predicts institutional trust

To test H2, I regressed institutional trust on perceived acquaintanceship network exposure, controlling for network size and other attributes (see Table 2 for the final, parsimonious model, Table S16 for stepwise models). Intra-class correlations show that only a low proportion of the variance is between provinces.

Model 1 (see Table S16) only included the network predictors. Results revealed that people with larger networks trusted institutions more. With equal network size, knowing more people in economically distressed conditions was significantly associated with lower institutional trust, while knowing more people in favourable conditions was associated with higher institutional trust. The interaction between exposure to distress and exposure to wellbeing (Model 2) was statistically not significant. So, their effects are independent.

Model 3, which only included non-network predictors, revealed that older people, university graduates, students, left-wing-oriented individuals, and members of multiple associations had higher institutional trust. Provincial GDP was unrelated to institutional trust (cf. Van der Meer, 2017). Model 3 (Table S16; non-network variables) had a pseudo-$R^2$ of.20, compared to.13 for Model 1 (networks).

Model 4 combines network exposure with these non-network attributes. This control slightly attenuated the network coefficients of earlier models but maintained their significance. Thus, with equal individual attributes (including age, political orientation), GDP, and network size, network exposure to economic distress was related to significantly lower institutional trust, and vice versa for exposure to favourable economic conditions, confirming H2. While networks

**Table 3** Overview of support for Hypothesis 1

| *Explanatory →* | Respondent unemployed | Respondent's education | Respondent's income | Respondent's age |
|---|---|---|---|---|
| *Dependent ↓* | H1a: | H1b: | H1c: | H1f: |
| *N* job loss | + | – | – | – |
| *N* first job | + | – | – | – |
| *N* evicted | + | – | – | – |
| *N* return parents | + | – | – | – |
| | | H1d: | H1e: | |
| *N* labour migrants | + | + | + | – |
| *N* self-employed | + | + | + | – |

*Note:* Cells indicate *expected* relationships: '+' indicates positive and '–' negative associations; colours indicate whether observed associations agreed with expected: blue indicates that the results supported the hypothesis (significantly and in expected direction); white that the observed association was non-significant; and red that the observed association was significant but in the opposite direction than expected (i.e. negative).

correlate with provincial GDP, their effect on trust is independent. When GDP was substituted by three alternative provincial attributes (Table S17), only lower eviction rates significantly predicted institutional trust, but network variables remained highly significant. Thus, institutional trust is shaped not only by individuals' own conditions but also by what they observe among the people surrounding them.

As a robustness check, Spearman correlations (Table S21) revealed that network exposure was significantly correlated with trust in *all* institutions –negatively for distress and positively for wellbeing– except for the correlation between economic wellbeing and trust in churches.

## Conclusions

### Empirical conclusions

While research relates macro-economic performance to citizens' institutional trust through their subjective evaluations, the formation of these evaluations remains understudied. This study, conducted at the end of the financial crisis in Spain, examined the role of social networks in shaping institutional trust, particularly through network exposure to economic distress. The findings reveal substantial network exposure to economic distress, with notable variations across dimensions. While only 10 per cent of individuals reported not knowing anyone who had become unemployed, most knew at least five people who had lost their jobs in the past three years, even if they had not experienced job loss themselves. The low overdispersion in this dimension contrasts with DiPrete et al's (2011) findings, probably due to Spain's skyrocketing unemployment rate at the time of the survey (versus 4–5% in the US in 2006)[5]. Most respondents also had acquaintances who were looking for their first jobs, had found jobs, had migrated for work, and had returned to their parental homes, although to varying degrees. In contrast, few respondents (20 per cent) reported knowing someone who had been evicted. As evictions were widespread, this result suggests '*transmission error*', where individuals lack knowledge of their acquaintances having been evicted.

Hypothesis 1 posited that *individuals with lower socioeconomic status (SES) and age have higher network exposure to economic distress, controlled for network size*. While bivariate descriptive analyses supported this, multivariate analyses revealed more complex patterns (see Table 3). For instance, I hypothesised that lower-educated individuals (H1b) would know more people who had lost their jobs, were unemployed and looking for their first jobs, had been evicted, or had to return to their parental homes. I found that they were indeed less exposed to economic wellbeing (finding jobs, having second homes, leaving the parental home) and coping mechanisms (self-employment, migration) than higher-educated individuals. However, contrary to my hypothesis, they were *not* more exposed to economic distress, except eviction. This complexity underscores the need to analyse intersecting attributes of stratification simultaneously. After controlling for individual and provincial characteristics, only age was consistently related to all forms of economic distress. This suggests that young people were not only disproportionally affected by the crisis but also disproportionally surrounded by others experiencing hardship. Overall, the results support the assumption that the hundreds of people we encounter in daily life –at work, the schoolyard, or gym–, are not representative cross-sections of society but biased toward our own attributes.

Second, I assessed whether uneven network exposure explained variance in institutional trust. As hypothesised (H2), respondents more exposed to economic distress through their networks had less confidence in institutions responsible for addressing the population's needs. Conversely, network exposure to favourable conditions was associated with higher trust. These two effects were independent and remained robust after controlling for individual and province-level attributes, underscoring their relevance.

In summary, network exposure to economic conditions is related to the formation of institutional trust during financial crises. Thus, social networks seem to play a significant role in shaping public opinion, beyond their other roles during the crisis, such as providing social support (Lubbers *et al.*, 2020). This novel finding has important theoretical implications for trust research.

### Theoretical implications

Based on the cognitive mechanism of social inference, I expected that networks with homogenising tendencies shape the macro-micro link connecting a country's economic performance to individuals' perceptions of that performance and, consequently, their trust in institutions. Metaphorically, networks were thus expected to act as prisms (Podolny, 2001), filtering the light differently depending on where you stand (i.e. shaping one's views on institutions differently, depending on your position in networks). The results are compatible with these expectations and underscore the importance of network homogeneity for understanding institutional trust.

We can extrapolate several theoretical expectations for future research from these findings. When networks display random mixing in economically unequal societies, we can expect that they contribute to a uniform public perception of the severity of economic crises. The negative experiences and emotions of one segment of society may be uniformly amplified across the network, and the larger this section is, the more those who have not personally experienced economic distress may feel vulnerable to it. This amplification may lower trust and generalise anxiety, but it can also foster solidarity and collective efficacy. Conversely, in unequal societies characterised by high network homogeneity, exposure to economic distress is uneven, potentially polarising public perceptions of financial crises. Some population segments may witness widespread poverty, evictions, and strained food banks, leading to low institutional trust. Meanwhile, others might observe resilience and continued economic wellbeing within their networks, resulting in sustained institutional trust. Cross-national and longitudinal designs incorporating networks and trust are needed to explore these dynamics and their causality further. Additionally, future research should consider more fine-grained network mechanisms, such as social comparison, which may affect how individuals process information from their networks.

Furthermore, the results challenge the predominant focus in trust research on a country's *average* trust as an indicator of macro-level cohesion, often overlooking the *variation* in trust within a population or between social groups. Low variation suggests that citizens share similar views on society, contributing to their collective consciousness (Durkheim 1893), which suggests another form of cohesion.

Future research may also re-evaluate some individual and macro-level factors traditionally associated with institutional trust using a network lens. For instance, research has found that more open and extroverted individuals trust their governments *less* (Citrin and Stoker, 2018). A network model would acknowledge that people with these personality traits tend to have larger and more diverse social networks (Pollet, Roberts, and Dunbar, 2011; Selden and Goodie, 2018), potentially exposing them to more varied life conditions. Consequently, the variation in trust attributed to stable personality traits might reflect the distinct positioning of different personalities in social networks, suggesting that rather than a personality issue, (dis) trust is a learned response to particular experiences.

This research also expands our understanding of acquaintance networks by showing that their homogeneity is associated with individuals' perceptions of the world. To strengthen future research in this line, I will conclude by discussing the limitations of the analytical approach used in this paper and propose a potential solution for future studies.

## Methodological development

The NSUM-based methodology for measuring network exposure can be easily implemented in surveys, enabling comparison across nations, time periods, and social categories (e.g. race and social status). However, this study has shown that transmission errors can distort overdispersion as a measure of homogeneity (Zheng *et al.*, 2006; DiPrete *et al.*, 2011). People typically know their acquaintances' names, genders, and races, but may be unaware of their economic circumstances. Following the Thomas theorem, DiPrete and colleagues (2011) argued that individuals are unlikely to be influenced by what they do not know about their network members' lives: It is the perception that matters. However, knowing how these perceptions map onto actual networks is crucial for understanding whether trust is influenced by networks or perceptions partly based on other features. Controlling for transmission errors requires knowing their magnitude (Maltiel *et al.* 2015).

Additionally, NSUM only collects aggregate relational data, which do not reveal the nature of relationships (e.g. tie strength, valence, relationship type). Nonetheless, relationship-level data could provide deeper insights into the mechanisms and conditions of social inference. Furthermore, without relationship data, it is difficult to assess the overlap between social groups, such as unemployed individuals who have been evicted.

To overcome these limitations, researchers can combine NSUM with 'name interpreters' from personal network analysis (i.e. questions about the type, strength, or other attributes of each nominated relationship). Similar to personal network studies, researchers can follow up on NSUM questions when respondents recall at least one person in a subpopulation. First, by following up on a set of *names* ('How many people do you know whose name is...?'), researchers can collect relationship data about a random sample of acquaintances if the names are relatively rare and jointly representative of the gender and age distributions in the population (McCarty, Bernard, Killworth, 1997)[6]. Asking respondents about these people's attributes (e.g. 'Was Sally ever evicted?') and how certain they are about their assessments can help estimate and control for transmission error. Second, following up on *social groups* (e.g. 'How many people do you know who were evicted?') allows researchers to collect relationship-level data (e.g. closeness, relationship type, valence) on purposive samples of ties in acquaintanceship networks, such as those experiencing economic distress. This approach can also examine whether social groups overlap. Refining this methodology offers significant promise for future research on network exposure and trust.

## Notes

1 Data, questionnaire, and sampling methodology available via CIS, http://www.cis.es/en/inicio (Study 3036, "Cohesión social y confianza").

2 Response patterns were considered inconsistent if the number of relatives and friends with a name exceeded the total

number of acquaintances with this name, on one or more occasions, by three or more in total. Smaller inconsistencies were corrected by adjusting the total number of people known with certain names to match the sum of friends and relatives.

3 The survey measured whether respondents lived with a partner and/or children, and the first four children's ages. Following standard practice, consumption units were reconstructed by counting the respondent as 1, each co-living person ≥14 years as 0.5, and children <14 as 0.3. This measure is conservative because most categories included 'with or without other relatives', who were not counted, unless respondents indicated living *only* with parent(s) or sibling(s), in which case a second adult was counted. Monthly net income (categorised) was crossed with consumption units to determine respondents' positions relative to the extreme poverty line (40 per cent of the median income per consumption unit in Spain), using data from the National Institute of Statistics of 2015 about 2014.

4 For confidentiality, CIS excluded individuals' municipalities and census tracts for populations <100,000, preventing the use of additional levels. As the number of municipalities far exceeds the number of respondents (see Sample), a two-level model is adequate.

5 Bureau of Labor Statistics (Current Population Survey).

6 If respondents recall multiple persons, a decision rule can avoid biasing tie strength.

## Supplementary Data

Supplementary data are available at *ESR* online.

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## Data availability

The data used in this paper are available from the Center for Sociological Research in Spain (Centro de Investigaciones Sociológicas, or CIS), and can be freely downloaded from their website (via the catalogue of studies) for non-commercial use under certain conditions, see https://www.cis.es/en/inicio. The study's archive number is 3036, and the title is 'Cohesión social y confianza'.

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