Trust and Turnout: A Network Approach to Understanding the Role of Social and Political Trust in Voter Participation

Chiara Richardt, Rutger Neeleman, Eva-Maria Vogel

University of Amsterdam

7205RM33XY: Network Analysis

Tessa Blanken, Ria Hoekstra

20.12.2024

Trust and Turnout: A Network Approach to Understanding the Role of Social and Political Trust in Voter Participation

Trust in each other and political institutions could be considered a vital aspect of social and political cooperation (Devine, 2024). Cultural theories hypothesise that trust is essential to democracies because it represents citizens' perception of democratic stability and functioning. (Mishler & Rose, 2005). Citizens with higher trust seem to engage more in political discussion, elaborate more on their political thinking, are less prejudiced, and vote more in political elections (Liu et al., 2018). However, since the 2008 financial crisis, in many Western democracies, trust in political institutions has declined (Coromina & Bartolomé Peral, 2020). This decrease in public trust in government, media, and NGOs explains the distrust in established parties and the rise of populist parties offering "simple solutions to complex problems" (Sasaki, 2019, p. 77).

A growing body of literature suggests that trust is related to voter turnout (i.e., the participation rate in an election) (e.g., Addeo et al., 2024; Devine, 2024). To explain the influence of trust on voter turnout, a distinction between political and social trust is necessary. (Addeo et al., 2024). Political trust, which covers trust in politicians, parties, and institutions, is related to a higher voter turnout (e.g., Cox, 2003; Grönlund & Setälä, 2007). A recent meta-analysis of 61 studies by Devine (2024) showed that political trust had a small-to-moderate effect on voter turnout. Similarly, low trust as a result of corruption has been shown to lead to lower election participation (Stockemer et al., 2013).

Still, not all studies find a direct effect of political trust on voter turnout. First, the relationship between social trust ("*trust towards 'the others'*") (Addeo et al., 2024, p. 24), and voter turnout seems to be context-dependent, with social trust outplaying the effect of political trust in national elections (Addeo et al., 2024). Second, Wang (2016) finds that the effect of political trust on voter turnout might be indirect or even nonexistent.

To address this knowledge gap about the potential interplay of social and political trust in influencing voters' decisions, we estimate a network model to investigate which trust items are the best predictors for voter turnout. Firstly, we will assess the structure of the estimated network to see whether it aligns with the types of trust identified by the literature (social vs. political) and how these clusters interact.

Secondly, we evaluate the connectivity of the network and the most central nodes. In an analysis of Causal Attitude Networks (CAN), Dalege et al. (2020) found that highly connected networks are better predictors of voting behaviours in the context of the US presidential election. Similarly, the most central attitude elements were most impactful in predicting voting behaviour. Consequently, evaluating the connectivity of our network and the most central attitude elements will provide insights into the overall predictive ability of the model and the most useful variables to predict voter turnout.

Methods

We estimated a Mixed Graphical Model (mgm; Haslbeck & Waldorp, 2020) using ten trust elements from the open-source dataset of the European Social Dataset (ESS ERIC, 2024) with a focus on the Netherlands (N = 1695). We included three social trust and seven political trust items as continuous nodes and the outcome variable 'vote' as a binary node in the network (Table 1).

Table 1

Trust and Outcome Variables Included as Nodes in the Networks

Variable	Item	Explanation	Scale
Social Trust	ppltrst	Most people can be trusted or you can't be too careful	0 = You can't be too careful; to 10 = Most people can be trusted
	pplfair	Most people try to take advantage of you, or try to be fair	0 = Most people try to take advantage of me; to 10 = Most people try to be fair
	pplhlp	Most of the time people helpful or mostly looking out for themselves	0 = People mostly look out for themselves; to 10 = People mostly try to be helpful
Political Trust	trstprl	Trust in country's parliament	0 = No trust at all; to 10 = Complete trust
	trstplt	Trust in politicians	
	trstlgl	Trust in the legal system	
	trstplc	Trust in the police	
	trstprt	Trust in political parties	
	trstep	Trust in the European Parliament	
	trstun	Trust in the United Nations	
Election Participation (Outcome)	vote	Voted last national election	1 = Yes 2 = No

To estimate our network, we used LASSO regularisation to prevent overfitting and spurious edges (Epskamp & Fried, 2018). We set the hyperparameter to 0, as we aim to discover and thus are more lenient in our estimation. Further, we used listwise deletion to deal with missing data. Edges between nodes represent direct associations between two nodes after controlling for all other nodes in the network. The network outcome analysis (NOA) by Blanken et al. (2020) allows us to interpret edges connected to the node 'vote' as predictive of voting behaviour, controlled for all other nodes.

We also conducted a centrality analysis for the metric closeness, which indicates the indirect connections of a node. The accuracy of our estimates and the centrality measures' stability was assessed using non-parametric and case-dropping bootstrapping, respectively. Additionally, the small-world index quantifies the global connectivity of the network.

Finally, we conducted a sensitivity analysis to check if the differing sample sizes for voters ($n = 1342$) and non-voters ($n = 213$) affect the network estimation. We randomly sampled 213 voters to have equal sample sizes and estimated a network for this subset of voters and all non-voters. Besides visual inspection, we ran a Network Comparison Test (NCT) where we compared each subsample network with the original network. Using an omnibus test, we examined if at least one edge differs across the networks. The global strength test examined if the overall level of connectivity is the same across networks. We repeated these steps ten times.

All analyses were performed in R (version 4.4.2; R Core Team (2024)) using the packages "bootnet" (Epskamp, Borsboom & Fried, 2018), "psychonetrics" (Epskamp, 2024), "qgraph" (Epskamp et al., 2012), and "NetworkComparisonTest" (van Borkulo et al., 2021).

Results

Visual Inspection

The visual inspection of our estimated network (Figure 1) provides two insights. First, we find only one edge that connects to our outcome variable ‘vote’, which is the edge between ‘pplfair - vote’. This means that controlled for all other trust items, whether people treat you fairly, is the only variable that is directly predictive of voting turnout. Second, we observe a cluster structure with social trust-related variables at the top-left of the network and political-trust-related items at the bottom. Both clusters have multiple edges within and few edges between them.

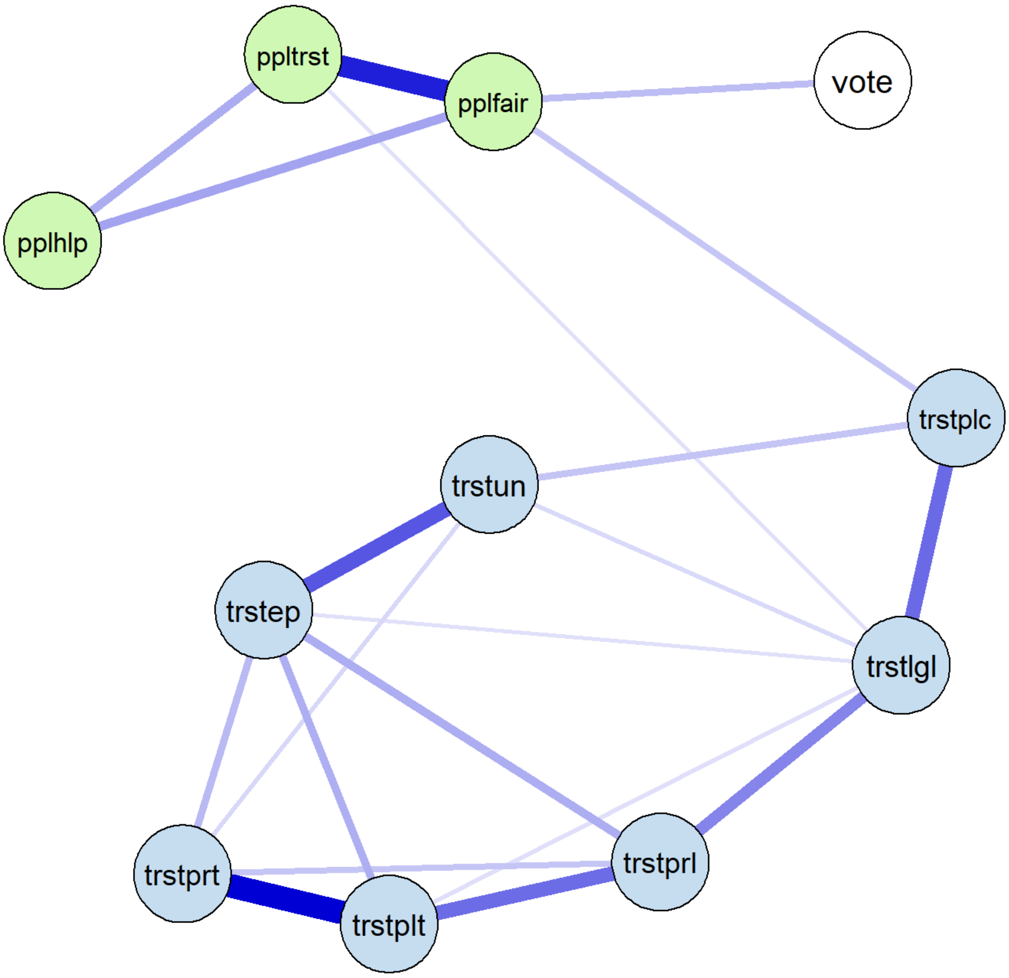
Connectivity & Centrality

Our network has a small-world index of 1.52, indicating that our network holds some small-world properties. This means that the network shows high global connectivity, which indicates that it is a good predictor of voting behaviour (Dalege et al., 2017).

Our accuracy test shows that our edge weights are stable. Visual inspection of Figure 2 shows that the bootstrapped confidence intervals are approximately equal in size, which indicates that the edge weight estimates are accurate. The correlation stability (CS) coefficient and Figure 3 indicate that the closeness estimates are not stable (CS = 0.05), meaning that closeness centrality cannot be reliably recovered in our network.

Figure 1

Estimated Network with Selected Items for Political Trust (blue), Social Trust (green) and Voter Turnout (white)



Note. The nodes are colored according to which category they belong: social trust = green; political trust = blue, and outcome = white. We plotted all network graphs with the maximum set to the highest edge weight of this graph (0.52). For the estimation of the network, we used the criterion “EBIC” and the AND-rule for edge selection. In our estimated network all edges are positive (blue). Thicker and more saturated edges refer to stronger connections between nodes. Abbreviations and their explanations can be found in Table 1.

Figure 2

Bootstrapped Mean and Sample Weights of Edges in Estimated Network Model

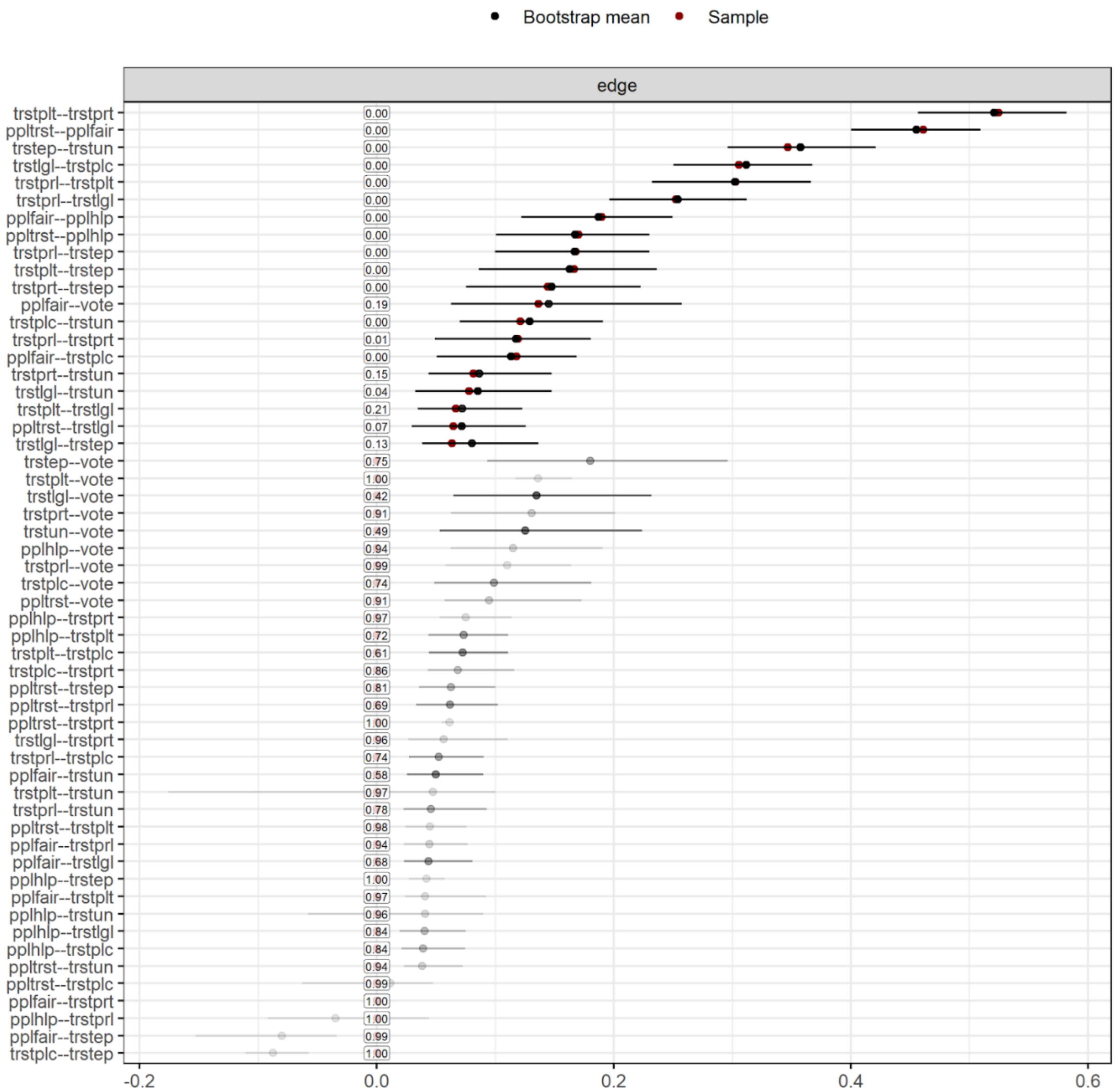
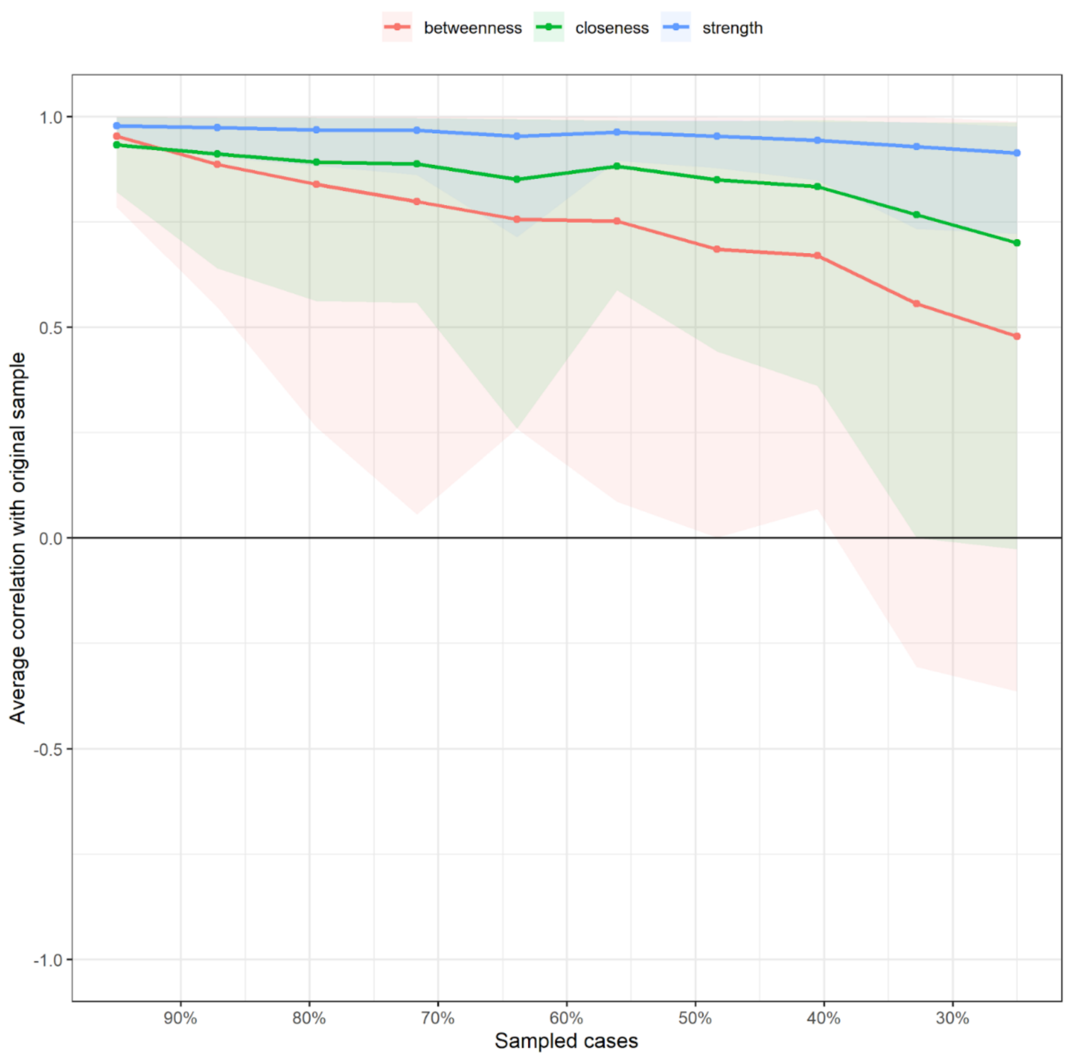


Figure 3

Case-dropping Bootstrap Plot that Checks for Stability of Centrality Estimates



Sensitivity Analysis

The sensitivity analysis revealed no significant differences in neither the omnibus nor the global strength test (all p > .05, Table 3 in Appendix B). This indicates that there are no significant differences in global structure or any edges between the subsamples and the original sample. However, visual inspection shows that – while the overall structure appears to be similar across networks – some edges are present/absent in the subsample networks that are not present/absent in the original network (Appendix B). Thus, we conclude that while the overall structure appears to be relatively stable, individual edges should be interpreted with caution.

Discussion

With the estimated network, we aimed to explore the relationship between social trust and political trust on voter turnout. The visual inspection revealed that items are clustered around their respective concept, with distinct clusters showing social trust and political trust. While the estimated edges show that only one social trust item is significant in predicting voter turnout, the cluster structure emphasises that the trust items are in a positive reinforcing relationship with each other, which means that targeting social trust generally could potentially increase election participation.

The highly connected clusters align with the overall networks' high global connectivity. Since highly connected networks serve as better predictors of political outcomes, such as voting behaviour (Dalege et al., 2017), the present network model appears suitable for analysing trust's influence on voter turnout.

To assess which item in the network has the biggest impact on voting, we assessed node-centrality. Since the closeness centrality was not stable, an interpretation of centrality in line with Dalege et al. (2017) was not possible.

While this novel approach of applying a NOA to CAN helps us assess the ability of attitude networks to model political outcomes, it also has some limitations. An inherent limitation of assessing voter turnout is the skewedness of the data, as the turnout for most national elections is well above 70% (ElectionGuide, n.d.), leaving only a small representation of non-voters in datasets. We addressed this using a sensitivity analysis. Even though the NCT indicated no significant differences between networks, the visual inspection of different networks painted a more ambiguous picture. Since the non-voter group (N = 216) was relatively small and mgm uses a listwise deletion approach for missing data, the insignificant NCT could also be a result of low power. Thus, future research should replicate our findings with a larger and (more) equally distributed sample.

Overall, our network revealed that voter turnout is correlated with social trust, which in turn is positively related to political trust. This aligns with recent literature suggesting social trust as a mediator for the relationship between political trust and election participation (Dinessen et al., 2022). This potential mediation could explain why the influence of political trust generally found by the literature (Devine, 2024) vanishes when controlling for social trust, but more confirmatory research isolating this mediation should be conducted.

References

Addeo, F., Ammirato, M., Paoli, A. D., Fruncillo, D., & Maddaloni, D. (2024). *Voter turnout: Overtime and regional trends in Europe*. Working paper no. https://www.truedemdata.eu/truedem/D2.3.Voter_Turnout_Overtime_and_Regional_Trends_in_Europe_29_02_2024.pdf

Blanken, T. F., Borsboom, D., Penninx, B. W., & Van Someren, E. J. (2020). Network outcome analysis identifies difficulty initiating sleep as a primary target for prevention of depression: A 6-year prospective study. *Sleep*, *43*(5), zsz288. https://doi.org/10.1093/sleep/zsz288

Coromina, L., & Bartolomé Peral, E. (2020). Comparing alignment and multiple group CFA for analysing political trust in europe during the crisis. *Methodology*, *16*(1), 21–40. https://doi.org/10.5964/meth.2791

Cox, M. (2003). When Trust Matters: Explaining Differences in Voter Turnout.

Dalege, J., Borsboom, D., van Harreveld, F., van den Berg, H., Conner, M., & van der Maas, H. L. J. (2016). Toward a formalized account of attitudes: The Causal Attitude Network (CAN) model. *Psychological Review*, 123, 2–22.

Dalege, J., Borsboom, D., van Harreveld, F., Waldorp, L. J., & van der Maas, H. L. J. (2017). Network Structure Explains the Impact of Attitudes on Voting Decisions. *Scientific Reports*, 7, Article 4909. https://doi.org/10.1038/s41598-017-05048-y

Devine, D. (2024). Does Political Trust Matter? A Meta-analysis on the Consequences of Trust. *Political Behavior*, *46*(4), 2241–2262. https://doi.org/10.1007/s11109-024-09916-y

Dinesen, P. T., Sønderskov, K. M., Sohlberg, J., & Esaiasson, P. (2022). Close (Causally connected) cousins? *Public Opinion Quarterly*, *86*(3), 708–721. https://doi.org/10.1093/poq/nfac027

ElectionGuide. (n.d.). *India*. Retrieved December 18, 2024, from https://www.electionguide.org/countries/id/152/

Epskamp S (2024). _psychonetrics: Structural Equation Modeling and Confirmatory Network Analysis_. R package version 0.13, <https://CRAN.R-project.org/package=psychonetrics>.

Epskamp S., & Fried EI. (2018) A tutorial on regularized partial correlation networks. *Psychol Methods*; doi:10.1037/met0000167.

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior research methods, 50*, 195-212.

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., Borsboom, D. (2012). qgraph: Visualizations of Relationships in Psychometric Data. Journal of Statistical Software, 48(4), 1-18. http://www.jstatsoft.org/v48/i04/.

European Social Survey European Research Infrastructure (ESS ERIC) (2024) ESS round 11 - 2023. Social inequalities in health, Gender in contemporary Europe. *Sikt - Norwegian Agency for Shared Services in Education and Research*. https://doi.org/10.21338/ess11-2023.

Grönlund, K., & Setälä, M. (2007). Political Trust, Satisfaction and Voter Turnout. *Comparative European Politics*, *5*(4), 400–422. https://doi.org/10.1057/palgrave.cep.6110113

Haslbeck, J. M. B., & Waldorp, L. J. (2020). mgm: Estimating Time-Varying Mixed Graphical Models in High-Dimensional Data. *Journal of Statistical Software, 93*(8), 1–46. https://doi.org/10.18637/jss.v093.i08

Ising, E. (1925). Beitrag zur Theorie des Ferromagnetismus. *Zeitschrift für Physik*, 31, 253–258.

Liu, J. H., Milojev, P., Gil De Zúñiga, H., & Zhang, R. J. (2018). The Global Trust Inventory as a “Proxy Measure” for Social Capital: Measurement and Impact in 11 Democratic

Societies. *Journal of Cross-Cultural Psychology*, *49*(5), 789–810. https://doi.org/10.1177/0022022118766619

Mishler, W., & Rose, R. (2005). What Are the Political Consequences of Trust?: A Test of Cultural and Institutional Theories in Russia. *Comparative Political Studies*, *38*(9), 1050–1078. https://doi.org/10.1177/0010414005278419

R Core Team (2024). _R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>.

Sasaki, M. (2019). *Trust in Contemporary Society*. BRILL. https://doi.org/10.1163/9789004390430

Stockemer, D., LaMontagne, B., & Scruggs, L. (2013). Bribes and ballots: The impact of corruption on voter turnout in democracies. *International Political Science Review*, *34*(1), 74–90. https://doi.org/10.1177/0192512111419824

van Borkulo,C.D., van Bork, R., Boschloo, L., Kossakowski, J.J., Tio, P., Schoevers, R. A., Borsboom, D., Waldorp, L. J. (2021). Comparing network structures on three aspects: A permutation test. *Psychological Methods.* DOI: 10.1037/met0000476.

van der Cruijsen, C., <!>de Haan, J., & <!>van Rooij, M. (2023). *The Impact of High Inflation on Trust in National Politics and Central Banks* (SSRN Scholarly Paper No. 4330151). Social Science Research Network. https://doi.org/10.2139/ssrn.4330151

Wang, C.-H. (2016). Political trust, civic duty and voter turnout: The Mediation argument. *The Social Science Journal*, *53*(3), 291–300. https://doi.org/10.1016/j.soscij.2016.04.008

Appendix A

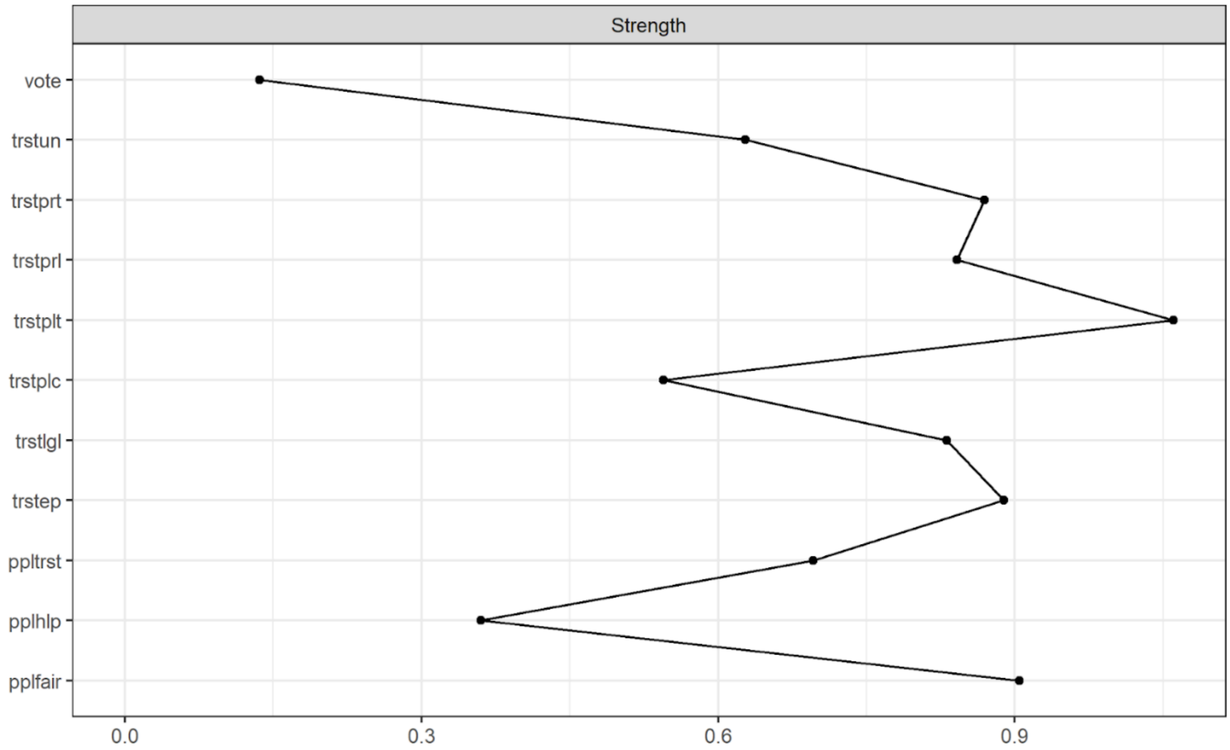
Table 2

Edge Weight Matrix Estimated Network

	ppltrst	pplfair	pplhlp	trstprl	trstplt	trstlgl	trstplc	trstprt	trstep	trstun	vote
ppltrst	0.00	0.46	0.17	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
pplfair	0.46	0.00	0.19	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.14
pplhlp	0.17	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
trstprl	0.00	0.00	0.00	0.00	0.30	0.25	0.00	0.12	0.17	0.00	0.00
trstplt	0.00	0.00	0.00	0.30	0.00	0.07	0.00	0.52	0.17	0.00	0.00
trstlgl	0.06	0.00	0.00	0.25	0.07	0.00	0.31	0.00	0.06	0.08	0.00
trstplc	0.00	0.12	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.12	0.00
trstprt	0.00	0.00	0.00	0.12	0.52	0.00	0.00	0.00	0.14	0.08	0.00
trstep	0.00	0.00	0.00	0.17	0.17	0.06	0.00	0.14	0.00	0.35	0.00
trstun	0.00	0.00	0.00	0.00	0.00	0.08	0.12	0.08	0.35	0.00	0.00
vote	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 4

Centrality Plot for Measure Strength



Appendix B

Table 3

Network Comparison Test Results

	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
Global Strength Test	0.86	0.89	0.99	0.93	0.68	0.78	0.87	0.97	0.87	0.87
Omnibus Test	0.89	0.98	0.88	0.99	0.90	0.23	0.73	0.82	0.90	0.86

Note. We conducted the NCT with 100 iterations for each run.

Figure 5

Sub_Net1

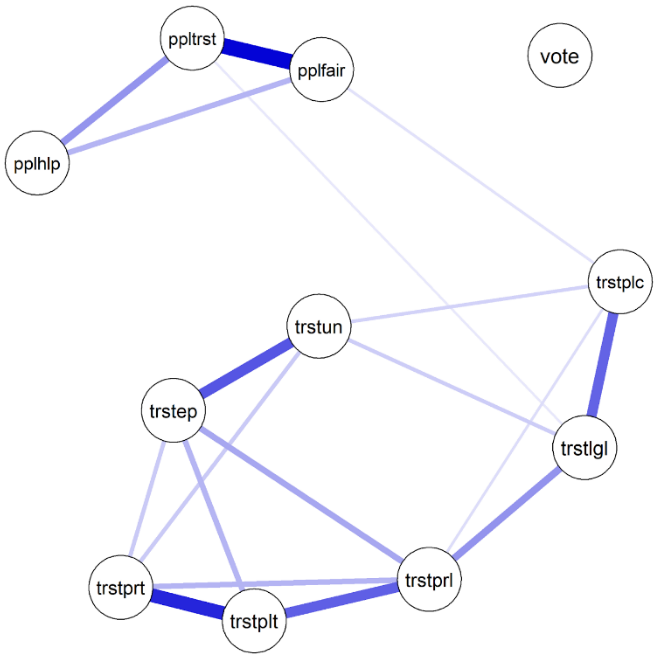


Figure 6

Sub_Net2

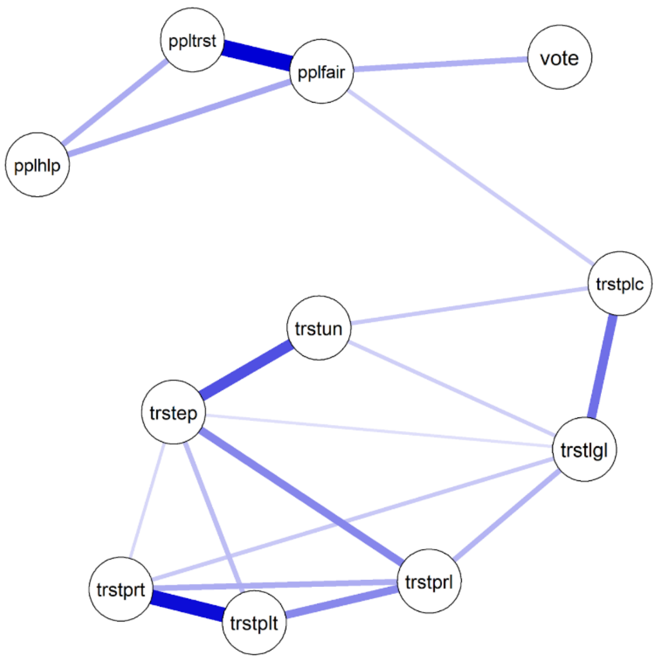


Figure 7

Sub_Net3

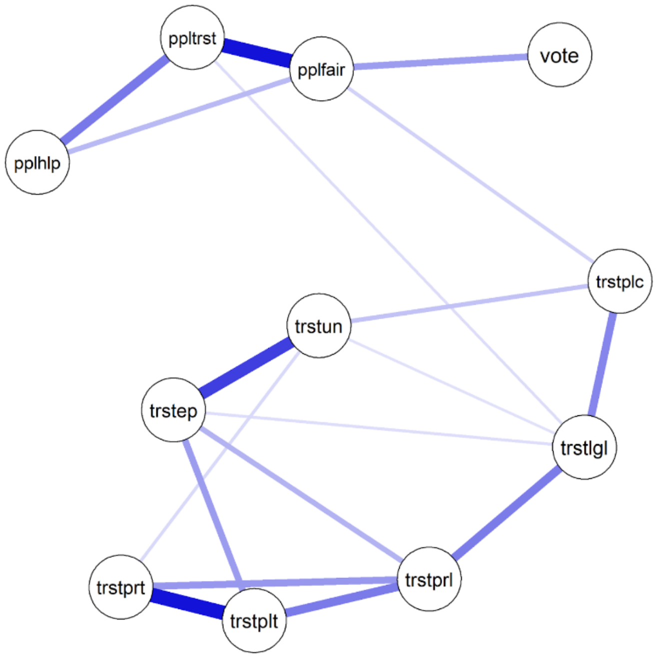


Figure 8

Sub_Net4

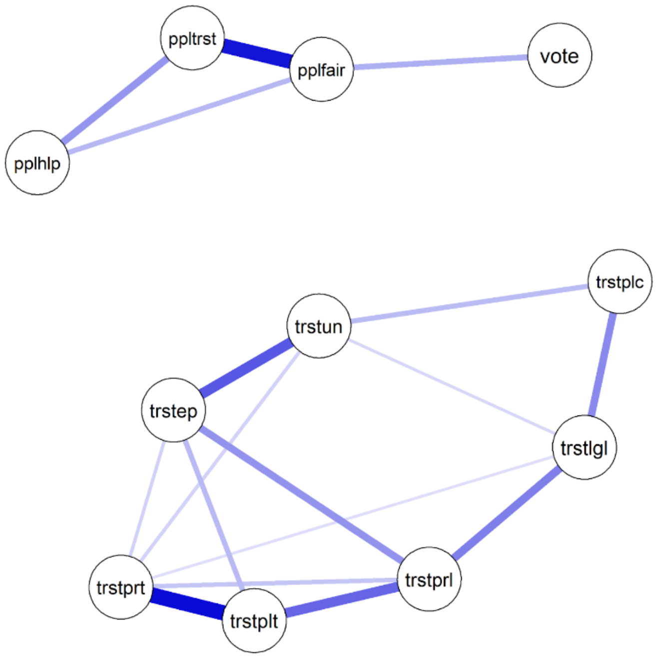


Figure 9

Sub_Net5

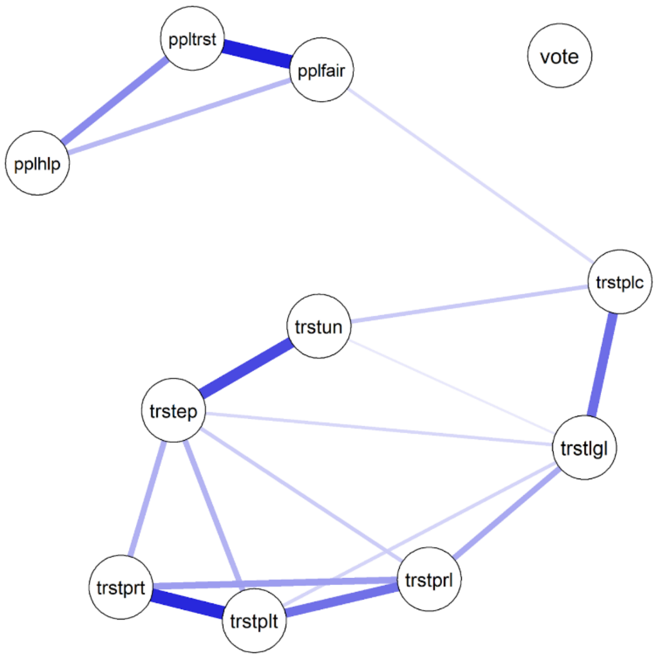


Figure 10

Sub_Net6

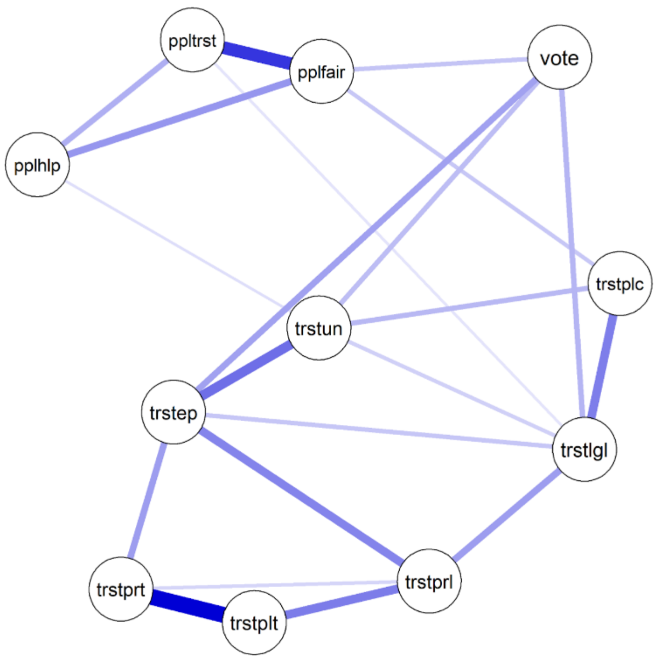


Figure 11

Sub_Net7

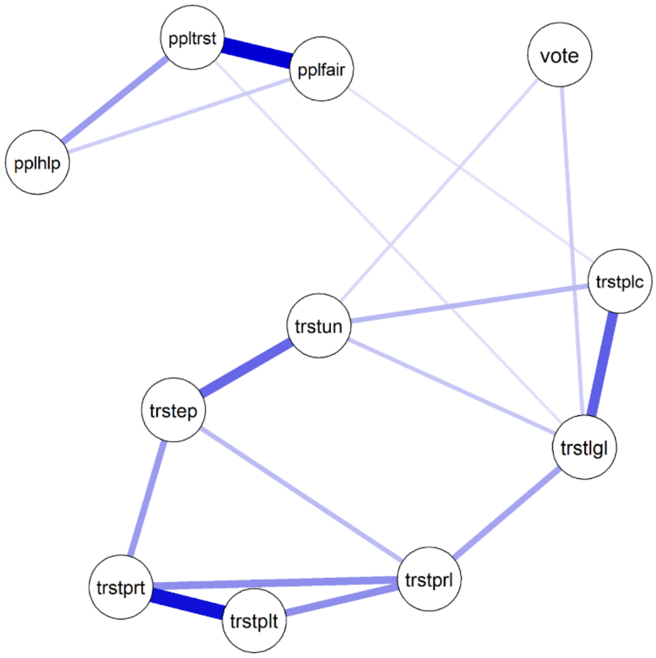


Figure 12

Sub_Net8

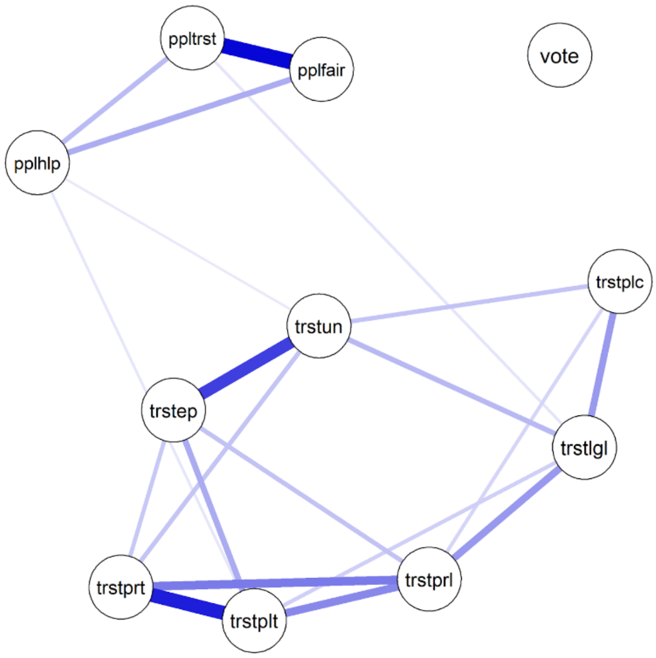


Figure 13

Sub_Net9

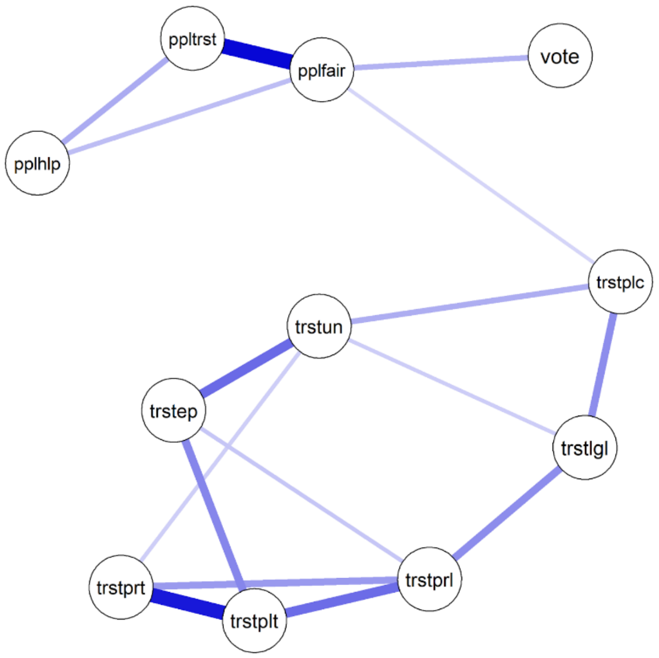


Figure 14

Sub_Net10