Exploring relationships between climate change beliefs and energy preferences: A network analysis of the European Social Survey

Mark Verschoor[1, *], Casper Albers[1], Wouter Poortinga[2, 3], Gisela Böhm[4, 5], and Linda Steg[1]

[1]Faculty of Behavioral and Social Sciences, University of Groningen, Groningen, the Netherlands

[2]School of Psychology, Cardiff University, Cardiff, Wales, United Kingdom

[3]Welsh School of Architecture, Cardiff University, Cardiff, Wales, United Kingdom

[4]Department of Psychosocial Science, Faculty of Psychology, University of Bergen, Bergen, Norway

[5]Department of Psychology, Inland Norway University of Applied Sciences, Lillehammer, Norway

[*]Corresponding author: Mark Verschoor, m.verschoor@rug.nl

Abstract

Understanding public attitudes to climate change and energy preferences is key to a successful transformation to a low-carbon society. While many studies have examined relationships between specific variables, little is known about the breadth of relationships between multiple climate and energy-relevant concepts. In this paper we used network models to explore and visualize relationships between climate change beliefs and energy preferences, using data from Round 8 of the European Social Survey (ESS8). ESS8 was conducted in 22 European countries and Israel. We found positive relationships between climate change salience, climate change beliefs, climate change concern, personal norm, and personal outcome expectancy, in line with prominent theories within the area. Moreover, beliefs on efficacy of actions of different actors (i.e., governments, large groups of people) to reduce climate change were positively related, and participants had consistent preferences for fossil energy sources or renewable energy sources, respectively. Furthermore, two types of energy security concerns could be distinguished, reflecting temporary and long term threats to energy security, respectively. Energy supply source preferences, energy policy support, and energy conservation behaviors were mostly not uniquely related to the other module variables. Furthermore, the relationships between variables, reflected in the network structure, were comparable across countries.

Keywords: energy sources, climate change, policy acceptability, visualization, European Social Survey, methodology, cross-country comparison

Exploring relationships between climate change beliefs and energy preferences: A network analysis of the European Social Survey

The way we produce and use energy contributes substantially to anthropogenic climate change (IPCC, 2018), resulting in global temperature increase, a loss of biodiversity, flooding, and more extreme weather events. Moreover, security of energy supply may be threatened, which implies that people may not always have access to energy due to, for example, technical failures (Poortinga, Aoyagi, & Pidgeon, 2013) or high financial costs (Weir, 2018). To address these challenges, consumers could more often engage in sustainable energy behavior, and accept sustainable energy sources and energy policies. An important question is to what extent climate beliefs and energy security beliefs are inter-related and linked to energy behaviors and energy preferences. We aim to address this question using data from Round Eight of the European Social Survey (ESS8; European Social Survey, 2016a).

ESS8 included a dedicated module on "Public Attitudes to Climate Change, Energy Security, and Energy Preferences" (European Social Survey, 2016b), which we refer to as the environmental module of ESS8. The module was designed on the basis of a conceptual framework that combined a number of common constructs and theories from environmental psychology, including the Value-Belief-Norm model (Stern, 2000), the climate scepticism framework typology (Rahmstorf, 2004), and the collective action model (Lubell, 2002). In this paper, extending previous research, we aim to understand relationships between variables included in this module that have not been studies together before, including climate change beliefs, climate change salience, energy security concerns, climate change concern, personal norm, efficacy beliefs, energy supply source preferences, energy saving behaviors, and energy policy supports (see Table 1 for an overview of the variables and their full wording).

It was expected that stronger climate change beliefs and climate change salience would be associated with a stronger concern about climate change, but that climate change beliefs and climate change salience would not be related to concerns about energy security as the latter merely addresses concerns about access to energy rather than the effects of energy use on climate change (see, e.g., Poortinga, Whitmarsh, Steg, Böhm, & Fisher, 2019). Specifically, it was expected that climate change concern would be higher when people believe climate change is real, caused by human action (rather than by natural phenomena), when they believe that climate change has mostly negative (rather than positive) consequences, and when climate change is salient to them (Bostrom et al., 2012; Poortinga, Spence, Whitmarsh, Capstick, & Pidgeon, 2011).

Next, both stronger climate change concern and energy security concerns were expected to strengthen a personal norm (i.e., a feeling of personal responsibility to act on climate change) and the belief that limiting one's own energy use will reduce climate change. A distinction was made between multiple dimensions of energy security concerns, including worry about power cuts, energy affordability, and too high dependence on energy imports and fossil fuel dependency, respectively. In addition, people indicated whether they were worried that energy supplies would be interrupted by natural disasters, insufficient power generation, technical failures, and terrorist attacks (see, e.g., Demski et al., 2018). We explored to which extent these different aspects of energy security were related as to understand whether people have a general tendency to be concerned about a wide range of factors threatening energy security, or whether they differentiate between different types of energy security concerns (see, e.g., Chester, 2010; Demski, Poortinga, & Pidgeon, 2014).

It was further assumed that stronger climate change beliefs, a stronger personal norm, higher climate change salience (cf. Rahmstorf, 2004), a stronger climate change concern (cf. Steg, De Groot, Drijerink, Abrahamse, & Siero, 2011), and stronger efficacy beliefs (cf. Lubell, 2002) would increase preferences for sustainable energy supply sources (and decrease preference for various types of fossil fuels and nuclear energy; cf. Demski et al., 2014), energy saving behaviors (e.g., energy efficiency behavior and energy curtailment behavior; cf. Gardner & Stern, 2002), and energy policy support (i.e., supporting fossil fuel tax, subsidizing renewable energy, and banning inefficient appliances; cf. Bostrom et al., 2012).

Following the collective action model framework (Lubell, 2002), the model included five types of efficacy beliefs reflecting personal efficacy, collective efficacy, and institutional efficacy beliefs. Specifically, the module included the belief that one is able to use less energy (self-efficacy), the belief that limiting one's own energy use will help reduce climate change (personal outcome expectancy), the belief that large number of people will limit their energy use to reduce climate change (collective efficacy), the belief that governments limit energy use to reduce climate change (institutional efficacy), and the belief that collective action by large numbers of people will reduce climate change (collective outcome efficacy; cf. Bandura, 1994; Koletsou & Mancy, 2011; Lubell, 2002; Steg & De Groot, 2010). We aimed to explore how these efficacy beliefs would be related, and to what extent each of these efficacy beliefs would be related to energy preferences. Moreover, we aimed to explore whether people have consistent preferences for energy supply sources, including fossiel energy, renewable, and nuclear energy sources. For example, a strong preference for renewables may be associated with a weak preference for fossil energy sources.

As yet, researchers typically investigate small parts of the ESS8. Indeed, several studies investigate relationships between a subset of variables included in the environmental and core modules in the ESS8, such as socio-political[1] and demographic[1] predictors of climate change beliefs (Poortinga et al., 2019), or relationships between variables from the environmental module and country-level variables, such as relationships between country characteristics1 and energy security concerns (Demski et al., 2018).

Such studies reporting part of the data from the environmental module provide important insights, but it would also be interesting to have an overarching view on relationships between variables included in this module, which may guide further (detailed) theory-building and analyses. The environmental module of the ESS8 enables us to get a comprehensive understanding of relationships between climate change beliefs, climate change salience, energy security concerns, climate change concern, personal norm, efficacy beliefs, energy supply source preferences, energy saving behaviors, and energy policy supports across Europe. We think there is great value in an overarching approach, as to understand whether more general factors, such as climate change beliefs, would also be related to specific energy preferences, or whether these relationships would be indirect, for example via personal norms. The ESS8 provides unique opportunities to test relationships between variables that are typically not studied together, and to test robustness of relationships across different countries and cultures. In this paper, we will perform an exploratory network analysis to get a more comprehensive understanding of the overarching relationships across the different variables of the environmental module of ESS8. We focus on the variables in the

[1]These data are part of the core module of ESS8 and not included in analyses in the present paper.

environmental module, rather than on all variables in the ESS8, as these variables allow us to increase understanding of the human dimension of energy.

Exploratory analyses are an important step in data analyses, because they yield an overarching insight in the data and relationships between variables. Most commonly, researchers investigate (bivariate) correlations to explore relationships between variables and to get a feel for the data. However, correlational tables are not without limitations. One limitation is that interpretability of these tables decreases as the number of included variables increases. For example, inspecting a few correlations is relatively easy, but investigating hundreds of correlations (465 in the environmental module) is overwhelming. Interpretation becomes even more difficult when correlational patterns in different groups (e.g., countries) are compared, especially when the number of groups is large; the ESS8 was conducted in 23 countries.

To explore relationships between the wide range of variables included in the environmental module that have not been studied together before, we present a methodological tool, the network model, that is suitable for exploring relationships between a large number of variables. It does so through easy-to-understand visualizations, in which main patterns in the data are immediately visible, whereas this is not the case in correlation tables. We want to stress that the present paper has an exploratory rather than a theory-testing nature. Similar to Bhushan et al. (2019), we will perform exploratory network analyses to investigate relationships between variables that are not commonly investigated together because they stem from different theories. Thus, we go beyond only investigating relationships between beliefs, attitudes, indicators of behavior and policy support, but we also look at relationships between all included items and concepts. Exploring relationships between these variables may result in new theorizing, that can be tested in follow-up research.

There are various ways to investigate whether certain constructs are related. For instance, one can create sum scores or work with factor analysis to find relationships between sets of variables. As an example, with factor analysis, one could analyze whether, and how much, disorders as general anxiety and depression are related. However, with factor analysis one cannot analyze which symptoms of anxiety and which symptoms of depression are strongest related. Alternatively, one can study correlations between individual items which can be done via the network approach. Network models provide a solution as network models do focus on individual variables and network models allow for easier inference than correlation matrices, which tend to get large and overwhelming when the number of included variables is large. We believe that one of the main benefits of our application of network models is that, while previous research has focused on relationships between various psychological constructs and behaviors, there have been few attempts at an overarching view of many concepts and their relationships (e.g., Bhushan et al., 2019).

Psychological network models were first introduced in the field of psychopathology (e.g., Borsboom & Cramer, 2013; Fried et al., 2018). Network models have been successfully employed to explore relationships between various concepts (e.g., beliefs, attitudes, anxiety and depression symptoms) in various subfields of psychology, including social psychology (Brandt, Sibley, & Osborne, 2019; Dalege et al., 2016; Dalege, Borsboom, van Harreveld, & van der Maas, 2019), clinical psychology (Fried et al., 2018), and environmental psychology (Bhushan et al., 2019). These papers, like ours, aimed to investigate relationships between variables of interest, to further develop theorizing in their fields. For instance, network analyses in psychopathology revealed that multiple disorders often have common symptoms. Symptoms that appear to be the link between two disorders are termed bridge nodes (e.g., Jones, Ma, & McNally, 2019). By specifically intervening on these bridge nodes in treatment, one minimizes the risk of comorbity, that is the risk that the presence of one disorder is causing the occurrence of the second disorder through these common symptoms. Thus, by studying the network one developed new theory to intervene in patients with certain disorders. Similarly, network analyses on the items included in the environmental module of ESS8 can result in new theorizing.

In the visualization of network models, variables (e.g., items included in a questionnaire) are represented by nodes, while the relationships between items are represented by lines (so-called edges). The thickness of the edges corresponds to the strength the relationships; the color of the edges indicates whether relationships are positive (blue) or negative (red). Variables that are closely related are usually located close to each other in the network (Fruchterman & Reingold, 1991), but the strength of relationships is reflected in the color and thickness of the edges, and not location in the graph.

The edges typically represent (regularized) partial correlations, which reflect the association between two items, controlling for the relationships between all other items included in the analyses. A partial correlation thus reflects the unique relationship between two items that cannot be explained by other variables in the data set. We like to point out that, at least in our case where we rely on cross-sectional data, the network is undirected which means that we only study correlations, not causal relations.

An advantage of network models is that they allow for investigating relationships between a wide range of variables that are derived from multiple, yet related, theories (Bhushan et al., 2019; Brandt et al., 2019; Dalege et al., 2016). Most psychological models focus on a small number of constructs, limiting their scope. The environmental module of ESS8 included multiple constructs that were derived form different related theories from environmental psychology. A network model approach allows to investigate relationships between variables included in different theories to be analyzed together, and can help identify variables that play a central role in the overall network. Solid understanding of such central variables can help building new (integrated) theories, and yield important practical implications as it indicates which variables could be an important target for policy as they are related to different relevant outcome variables.

Network models are well-suited to reveal which variables play a central role in the network, which implies that they are related to many other variables or strongly related to a few other variables. To investigate this concept of centrality, we investigate the node strength centrality measure (Freeman, 1978; Opsahl, Agneessens, & Skvoretz, 2010). A larger node strength corresponds to a more central variable. However, it is important that researchers keep theory and/or common sense in mind when investigating centrality, as a relatively non-central variable may still be important (Fried et al., 2018). For example, belief in the reality of climate change may not be a central variable in terms of node strength centrality because it is only related to the salience of climate change, but it may be relevant for the network as it may be indirectly related to many other variables through climate change salience.

We further aim to test how stable the resulting network is. Specifically, we will test network stability by examining whether the network remains similar when a large number of data points have been removed at random from the analyses. A highly stable network remains similar to itself when removing a large number of participants from the analysis, which implies that the resulting network is robust.

We extend previous exploratory network analyses by investigating cross-country similarities or differences in the network models corresponding to the different countries. We will investigate to what extent relationships between variables in the environmental module are comparable across countries in three ways. First, we perform a network analysis on the data of each of the 23 countries separately and conduct a visual inspection of the individual country networks. This provides a first insight into whether the networks are comparable. Second, we investigate the correlations between the node strengths per country and the node strengths of the network of the 22 remaining countries. Strong correlations indicate that a more central variable in one country also tends to be a more central variable in the other countries. Third, we investigate whether countries have similar network structures, by performing cluster analyses to examine whether there are clusters of countries where the relationships between variables are similar. The more clusters we find, the more the network structures may differ across countries. In contrast, fewer clusters imply that the overall network of relationships between variables in the environmental module are highly similar in different countries.

Summarized, this paper has two aims. First, we aim to examine how the different climate change beliefs, climate change salience, energy security concerns, climate change concern, personal norm, efficacy beliefs, energy supply source preferences, energy saving behaviors, and energy policy supports included in the environmental module of ESS8 are related to one another, and to identify which variables play a central role in the networks. Second, we aim to examine the extent to which the relationships between variables as reflected in the networks are similar across countries.

2. Method

2.1. Participants and procedure

Round 8 of the European Social Survey (ESS8) was conducted between August 2016 and December 2017, with data collection in the 23 individual countries usually taking place within a three-month period. Next to the core module that is administered every 2 years, ESS8 contained an environmental module: A dedicated module on climate change beliefs, energy security beliefs, and energy preferences. Interviews were conducted face-to-face in participants' own homes with people aged 15 years and over. The data set included 44,387 participants (47.4 % men, 52.6 % women, and 9 participants did not disclose their gender). The mean age of the participants was 49.14 years (range = 15-100, SD = 18.61). The full questionnaire and the European Social Survey Round 8 dataset can be downloaded from http://www.europeansocialsurvey.org (European Social Survey, 2016a). Detailed information about the data collection, including coding and software used in the different countries, can be found in the ESS8 Data Documentation Report (European Social Survey, 2016b). The unweighted descriptive statistics for the variables included in the environmental module for the individual countries are reported in Table 2[2].

[2]The weighted descriptive statistics are reported in Demski et al. (2018). The weighted descriptives statistics take into account different sample inclusion probabilities. We report unweighted descriptive statistics because we also report network analyses based on unweighted data. To the best of our knowledge, weighted network analyses are not yet possible.

Table 1

Label, short description, and full wording of all questionnaire items included in our network analyses.

Label	Description	Full wording
	Climate Change Beliefs	
CCB1	Climate change reality[a,*]	You may have heard the idea that the world's climate is changing due to increases in temperature over the past 100 years. What is your personal opinion on this? Do you think the world's climate is changing? Choose your answer from this card.
CCB2	Climate change cause[b]	Do you think that climate change is caused by natural processes, human activity, or both?
CCB3	Climate change impact[c,*]	How good or bad do you think the impact of climate change will be on people across the world? Please choose a number from 0 to 10, where 0 is extremely bad and 10 is extremely good.
	Climate Change Salience	
CCS	Climate change salience[b]	How much have you thought about climate change before today?
	Energy Security Concerns	
ESC1	Concern about energy reliability[b]	How worried are you that there may be power cuts in [country]?
ESC2	Concern about energy affordability[b]	How worried are you that energy may be too expensive for many people in [country]?
ESC3	Concern about import dependency[b]	How worried are you about [country] being too dependent on energy imports from other countries?
ESC4	Concern about fossil fuel dependency[b]	How worried are you about [country] being too dependent on using energy generated by fossil fuels such as oil, gas and coal?
ESC5	Concern about energy security due to natural disasters[b]	How worried are you that energy supplies could be interrupted by natural disasters or extreme weather?
ESC6	Concern about energy security due to insufficient power generation[b]	... and by insufficient power being generated?

ESC7	Concern about energy security due to technical failures[b]	... and by technical failures?
ESC8	Concern about energy security due to terrorist attacks[b]	And how worried are you that energy supplies could be interrupted by terrorist attacks?
	Climate Change Concern	
CCC	Climate change concern[b]	How worried are you about climate change?
	Personal Norm	
PN	Personal responsibility to reduce climate change[c]	To what extent do you feel a personal responsibility to try to reduce climate change?
	Efficacy Beliefs	
EB1	Self-efficacy[c]	Overall, how confident are you that you could use less energy than you do now?
EB2	Personal outcome expectancy[c]	How likely do you think it is that limiting your own energy use would help reduce climate change?
EB3	Collective efficacy[c]	How likely do you think it is that large numbers of people will actually limit their energy use to try to reduce climate change?
EB4	Collective outcome expectancy[c]	Now imagine that large numbers of people limited their energy use. How likely do you think it is that this would reduce climate change?
EB5	Institutional efficacy[c]	And how likely do you think it is that governments in enough countries will take action that reduces climate change?
	Energy Supply Source Preferences	
ESSP1	Preference for coal power[b]	First, how much of the electricity used in [country] should be generated from coal?
ESSP2	Preference for natural gas power[b]	And how about natural gas?
ESSP3	Preference for hydroelectric power[b]	And how about hydroelectric power generated by flowing water from rivers, dams and seas?

ESSP4	Preference for nuclear power[b]	How much of the electricity used in [country] should be generated by nuclear power?
ESSP5	Preference for solar power[b]	And how about sun or solar power?
ESSP6	Preference for wind power[b]	And how about wind power?
ESSP7	Preference for biomass power[b]	And how about biomass energy generated from materials like wood, plants and animal excrement?
	Energy Saving Behaviors	
ESB1	Energy efficiency behavior[c]	If you were to buy a large electrical appliance for your home, how likely is it that you would buy one of the most energy efficient ones?
ESB2	Energy curtailment behavior[d]	There are some things that can be done to reduce energy use, such as switching off appliances that are not being used, walking for short journeys, or only using the heating or air conditioning when really needed. In your daily life, how often do you do things to reduce your energy use?
	Energy Policy Supports	
		To what extent are you in favour or against the following policies in [country] to reduce climate change?
EPS1	Support fossil fuel tax[b,*]	Increasing taxes on fossil fuels, such as oil, gas and coal.
EPS2	Support subsidy renewable energy[b,*]	Using public money to subsidise renewable energy such as wind and solar power.
EPS3	Support ban least energy efficient appliances[b,*]	A law banning the sale of the least energy efficient household appliances.

*Note: a = 4; b = 5; c = 11; d = 6 answer options excluding refusal to answer and don't know. * indicates reverse-coded items.*

Table 2

Sample size and descriptive statistics for age and gender per country, unweighted.

Country	N	Mean age (SD)	Percentage female
Austria	2,010	49.32 (17.06)	53.88 %
Belgium	1,766	46.31 (18.31)	48.67 %
Czech Republic	2,269	46.44 (16.65)	49.54 %
Estonia	2,019	47.57 (18.37)	49.35 %
Finland	1,925	49.31 (18.36)	47.72 %
France	2,070	51.28 (18.23)	51.76 %
Germany	2,852	48.40 (18.25)	45.88 %
Hungary	1,614	50.15 (17.98)	55.14 %
Iceland	880	48.25 (17.53)	48.87 %
Ireland	2,757	49.17 (17.00)	47.94 %
Israel	2,557	45.15 (18.95)	46.44 %
Italy	2,626	46.70 (17.70)	47.09 %
Lithuania	2,122	48.83 (17.59)	56.50 %
Netherlands	1,681	50.62 (18.31)	51.90 %
Norway	1,545	47.06 (18.27)	44.22 %
Poland	1,694	44.26 (17.65)	48.64 %
Portugal	1,270	48.14 (17.39)	50.56 %
Russia	2,430	44.82 (17.57)	55.11 %
Slovenia	1,307	46.99 (17.81)	50.74 %
Spain	1,958	45.42 (15.88)	44.64 %
Sweden	1,551	51.58 (18.61)	45.81 %
Switzerland	1,525	47.48 (18.57)	45.27 %
United Kingdom	1,959	50.61 (18.32)	52.09 %
Overall	44,387	49.14 (18.61)	52.77 %

2.2. Variables

The environmental module in ESS8 covered nine different rubric concepts[3], namely (1) climate change beliefs, (2) climate change salience, (3) climate change concern, (4) energy security concerns, (5) personal norm, (6) efficacy beliefs, (7) energy supply source preferences, (8) energy saving behaviors, and (9) energy policy support. Table 1 shows the variables included and the exact questionnaire wording for all included items, as well as the rubric concepts and short descriptions that we use throughout this paper.

2.3. Data analyses

2.3.1. Missing data. Analyses were performed with pairwise deletion of missing data. Unusable responses for any reason (e.g., due to survey flow, an answer outside the possible range, refusing to answer, or not knowing an answer) were treated as missing data. These missing data may not be Missing Completely At Random. Participants (n = 1,327; 3 % of the total sample) who indicated that they believed that climate change is not real did not rate a number of items, namely climate change cause (CCB2), climate change impact (CCB3), climate change concern (CCC), personal responsibility to reduce climate change (PN), the likelihood that limiting one's own energy use will help reduce climate change (EB2), the likelihood that large numbers of people will limit their energy use (EB3), the likelihood that climate change would reduce if large numbers of people would limit their energy use (EB4), and the likelihood that governments in enough countries will take actions to reduce climate change (EB5).

[3]We like to stress that variables corresponding to the same rubric concept in ESS8 not necessarily reflect one single concept. For instance, the rubric concept of energy supply source preference includes, among others, preferences for coal power and wind power that do not correspond to the same construct.

2.3.2. Standardizing data. To prevent the possibility of country differences in means driving the overall network model and distorting the correlations (i.e., Simpson's paradox; Simpson, 1951), we standardized the data by rescaling all variables such that for each country every variable had a mean of 0 and a standard deviation of 1. Indeed, the unstandardized network (available on osf.io/85mah) shows some spurious negative correlations due to these differences in mean levels.

2.3.3. Network analyses. For all our analyses, we used unweighted data. We followed the common strategy of using Mixed Graphical Models (i.e., a type of network model suitable for variables measured on different scales) to visualize relationships between variables included in the ESS8 module (MGMs; Epskamp, Borsboom, & Fried, 2017; Lauritzen, 1996). Not all of our variables, for instance those with only a few answer possibilities (see Table 1 for an overview of the number of answer possibilities), can be assumed to be normally distributed. Some of our variables are treated as non-normally distributed because they have 7 or fewer answer possibilities. The qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012a) and bootnet (Epskamp et al., 2017) packages take this into account by computing correlations suited for ordinal variables (e.g., polychoric and polyserial correlations). Furthermore, inferences for correlations are known to be robust against violations of the normality assumption (Ernst & Albers, 2017; Williams, Grajales, & Kurkiewicz, 2013). Therefore, data transformations were not necessary. To prevent a large network model showing many small partial correlations that are relatively weak, we used a technique called regularization that forces small partial correlations to zero (Chen & Chen, 2009; Foygel & Drton, 2010; Friedman, Hastie, & Tibshirani, 2008;

Tibshirani, 1996)[4]. Using partial correlations together with regularization techniques in the context of network models reduces the number of relationships shown, filters out spurious effects, and reduces the likelihood of Type I errors. The resulting network of partial correlations is thus a relatively conservative network, where the presence of an edge indicates a unique relationship between variables.

The regularization technique facilitates the interpretation of the network model and facilitates the estimation of the model because fewer parameters need to be estimated. Despite this regularization, a network model may still include many small correlations, making it more difficult to interpret. To facilitate the interpretation, we removed weak correlations from the visualization. Specifically, we removed edges weaker than about .122 (corresponding to a unique explained variance of 1.5 % or less) from the visualization. For this data set, this cut-off provided a good balance between visual parsimony and completeness.[5] The combination of regularization (i.e., forcing particularly small correlations to zero) and sparse visualization (i.e., not showing any remaining small edges) often yields a more easily interpretable network, where the presence of an edge between variables may indicate a meaningful relationship. We used the default settings (i.e., EBICglasso regularization) in the R package *bootnet* (Epskamp et al., 2017) to estimate the networks, and *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012b) to visualize the networks. In this visualization, we gave items belonging to the same rubric concept the same color, which aids interpretation of the networks.

[4]For more details, as well as details regarding assumptions of network models, we refer to Epskamp et al. (2017).

[5]We have provided a visualization of the network with all edges, as well as code to create the network with a different cut-of on osf.io/85mah.

2.3.4. Centrality. In order to examine which variables are more strongly related to other variables (i.e., more central in the network), we computed the node strength centrality measures (node strength henceforth) that reflects the sum of the absolute values of all the (regularized) partial correlation coefficients (i.e., all edges) that a variable has. We used the R package bootnet (Epskamp et al., 2017) to compute the node strength of each variable (Freeman, 1978; Newman, 2010; Opsahl et al., 2010). We used node strength as our measure of centrality because this measure is generally the most stable and intuitively clear centrality measure (Epskamp et al., 2017). Node strength is not easily interpreted without context. For instance, for country X, the node strength of node Y was Z. Whether Z is large or small depends on many factors, including the sample size and the node strengths of the other nodes in the network. In order to facilitate cross-country comparison, we therefore standardized the node strengths. A standardized node strength of 0 implies an average strength. Negative standardized node strengths imply that the corresponding variables are, compared to the other variables in the network, less strongly than average related to the other variables. Positive standardized node strengths correspond to variables that are more strongly than average related to the other variables in the network[6]. To investigate network stability, we investigated whether node strengths change when random data were removed from the analyses. In a stable network, the node strengths and the ordering of variables based on node strength should not change much.

2.3.5. Country comparison. To examine whether the network structure is similar across countries, and thus whether the relationships between variables are

[6]In this paper, we compare strength values of nodes in the network; results of corresponding significance tests to compare the different node strengths are presented on osf.io/85mah.

similar across countries, we performed the following steps. First, we used bootnet to estimate a network model for each country separately, and we performed a visual inspection of these 23 country networks using the same node layout as the overall network. Second, to investigate the extent to which the node strengths are similar across countries, we computed Spearman's correlations between node strengths of each country's network and the remaining 22 countries. We use node strengths, rather than all edge weights, because in regularized networks the edge weight matrices contain a large percentage of zeroes, which would likely bias results. Third, we investigated whether and which countries are similar in network structure, by performing a k-means cluster analysis (MacQueen, 1967) on the country network models. A k-means cluster analysis is a suitable method for investigating similarity in network clusters across countries. Further motivation for k-means clustering in network models is given in (Krone, Albers, Kuppens, & Timmerman, 2018). We use the edge weight matrices of each country as input into the clustering algorithm. Countries that are clustered together have a similar network structure of relationships between variables in the environmental module in ESS8. Note that countries with similar relationships might still have dissimilarities with respect to the means and standard deviations of the items.

Using more clusters generally increase the proportion of explained variance, but using more clusters also generally increases the risk of overfitting to the data. We use the one-standard-error method (Tibshirani, Walther, & Hastie, 2001) to balance this tradeoff. This method investigates different cluster solutions and chooses the cluster solution that is, in model fit terms, at least one standard error better than the next cluster solution. We used the gap statistic (Tibshirani et al., 2001) to decide which number of clusters best describes the data. For technical details, we refer to (Tibshirani et al., 2001). For the exact implementation of these algorithms in the factoextra package, we refer to Kassambara and Mundt (2017a).

To test the robustness of our findings from the k-means cluster analyses, we also employed four other clustering techniques from the R package cluster (Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2017): the partitioning around medoids method, the clustering large applications method, the fuzzy analysis method, and the hierarchical clustering and cut the three method. The first three methods are used by the cluster package in R, and statistical details are described in (Kaufman & Rousseeuw, 1990, Chapter 2-4). The hcut-method is from the R package factoextra (Kassambara & Mundt, 2017). For all five methods, we initially used the gap statistic to decide upon the number of clusters. To further explore robustness of our results, we also evaluated the models with another criterium, namely the within sum of squares. The results of all 10 (5 algorithms $\times$ 2 evaluation methods) are visualized using the factoextra package (Kassambara & Mundt, 2017). All code and results are included on osf.io/85mah.

3. Results

3.1. Network analyses

The estimated network, for all countries together, based on regularized partial correlations is visualized in Figure 1. Nodes, corresponding to the different questionnaire items, are color-coded by their rubric concept. Figure 1 shows that preferences for renewable energy sources are positively related. Specifically, positive edges are shown between a preference for solar power (ESSP5), wind power (ESSP6), hydroelectric power (ESSP3), and biomass (ESSP7). The positive association between preference for wind power and solar power was the strongest of all edges. Furthermore, a positive association was found for a preference for coal (ESSP1) and natural gas

(ESSP2). No meaningful associations were found between preferences for renewable energy sources and fossil fuels. A preference for nuclear energy (ESSP4) was not related to preference for any of the other energy sources, and more generally, with any other item in the dataset.

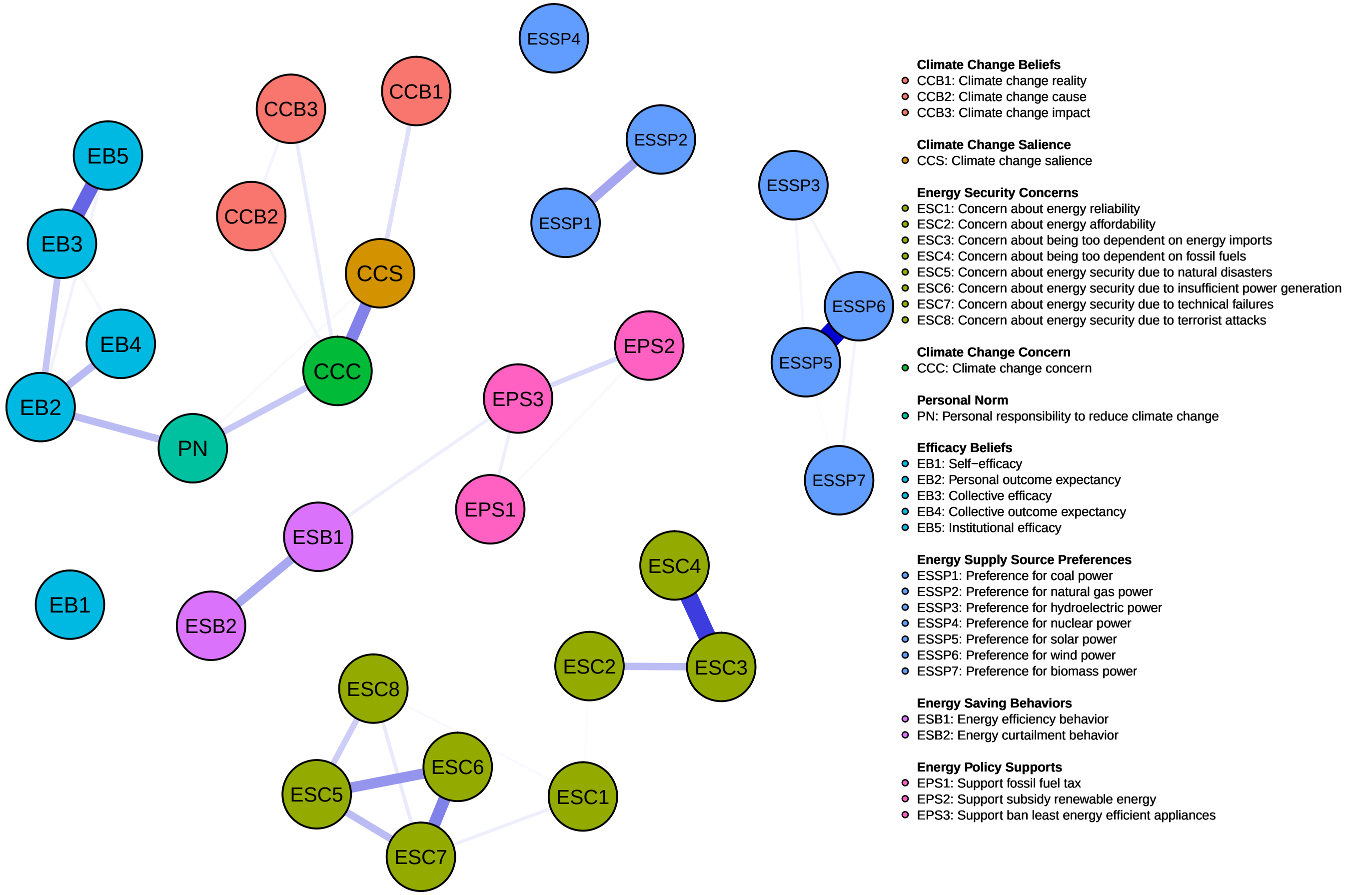

Figure 1. The estimated network for the full data set. Nodes are color-coded by rubric concept. A thicker edge corresponds to a larger regularized partial correlation. Blue edges reflect positive relationships and red edges reflect negative relationships.

There were relatively strong positive relationships between several of the energy security concern items. Specifically, a stronger concern about import dependency (ESC3) was related to a stronger concern about fossil fuel dependency (ESC4). Also, a stronger concern about lower energy security due to natural disasters (ESC5) was related to a stronger concern about energy security because of insufficient power being generated (ESC6) and a concern about energy security because of technical failures (ESC7). Concern about energy reliability due to power cuts was hardly related to the other energy security concerns.

Generally, efficacy beliefs were positively related with each other. There were particularly strong positive relationships between the belief that others will limit their energy use to reduce climate change (EB3) and the belief that governments in enough countries will take action to reduce climate change (EB5), and between the belief that climate change would reduce if many people would limit their energy use (EB4) and the belief that climate change would reduce if the participant would limit his/her own energy use (EB2). Yet, participants' belief that they could use less energy than they do now (self-efficacy; EB1) was not related to the other efficacy beliefs, nor to any other variable included in the network analyses.

Buying an energy efficient appliance (energy efficiency behavior; ECB1) was positively related with engagement in daily actions that would reduce energy use (energy curtailment behavior; ECB2), as well as with support for a ban of the least energy efficient appliance (EPS3). Furthermore, positive relationships were found between support for different types of energy policies: the more participants support a fossil fuel tax (EPS1), the more they support a ban of the least energy efficient appliances (EPS3) and a subsidy for renewable energy (EPS2).

3.1.1. Centrality. Figure 3 shows the standardized node strengths per variable (diamonds). Climate change concern (CCC) was the variable with the highest centrality score, and was related in particular to climate change salience (CCS). Climate change concern had weak relationships with feelings of personal responsibility to reduce climate change (PN), the belief that climate change is anthropogenic (CCB2), and the belief that climate change has negative consequences (CCB3). Personal responsibility to reduce climate change (PN) was the variable with the second highest node strength. The more people feel responsible to mitigate climate (PN), the more they have thought about climate change (CCS), and the more they think individual actions will be effective to mitigate climate change (EB5). The least central variables in the network were a preference for hydroelectric power (ESSP3) and a preference for biomass power (ESSP7). Both of these variables had no substantial relationships with any of the other variables.

3.1.2. Network stability. Stability analyses revealed that the overall network was stable. On osf.io/85mah, we illustrate the node strengths for the overall network and what happens to those when random data rows (i.e., data from randomly selected individuals) were removed from the analyses. As in Figure 3, the most central variables remain climate change concern (CCC) and personal responsibility to reduce climate change (PN). The node strengths of these variables decreased slightly as more data were removed from the analyses. The order of node strengths remains relatively stable too, which means that the node strengths have been estimated accurately and that the network is very stable.

3.2. Country comparison

To compare the network structure across countries, we first visually inspected every country network. Network visualizations of four randomly selected countries are shown in Figure 2 as illustration; all other network visualizations are included at osf.io/85mah. The network visualizations revealed that, while there are some small differences between countries, the network models are generally very similar. We examined differences in the range and variance in node strengths per country by visualizing them as small circles on the same line as the node strengths included in the overall network (see Figure 2). To quantify the similarity between node strengths across countries, we computed 23 (Spearman's) correlations between the node strengths per country and the node strengths of the network of the remaining 22 countries (see osf.io/85mah). The median correlation between node strength was .821.

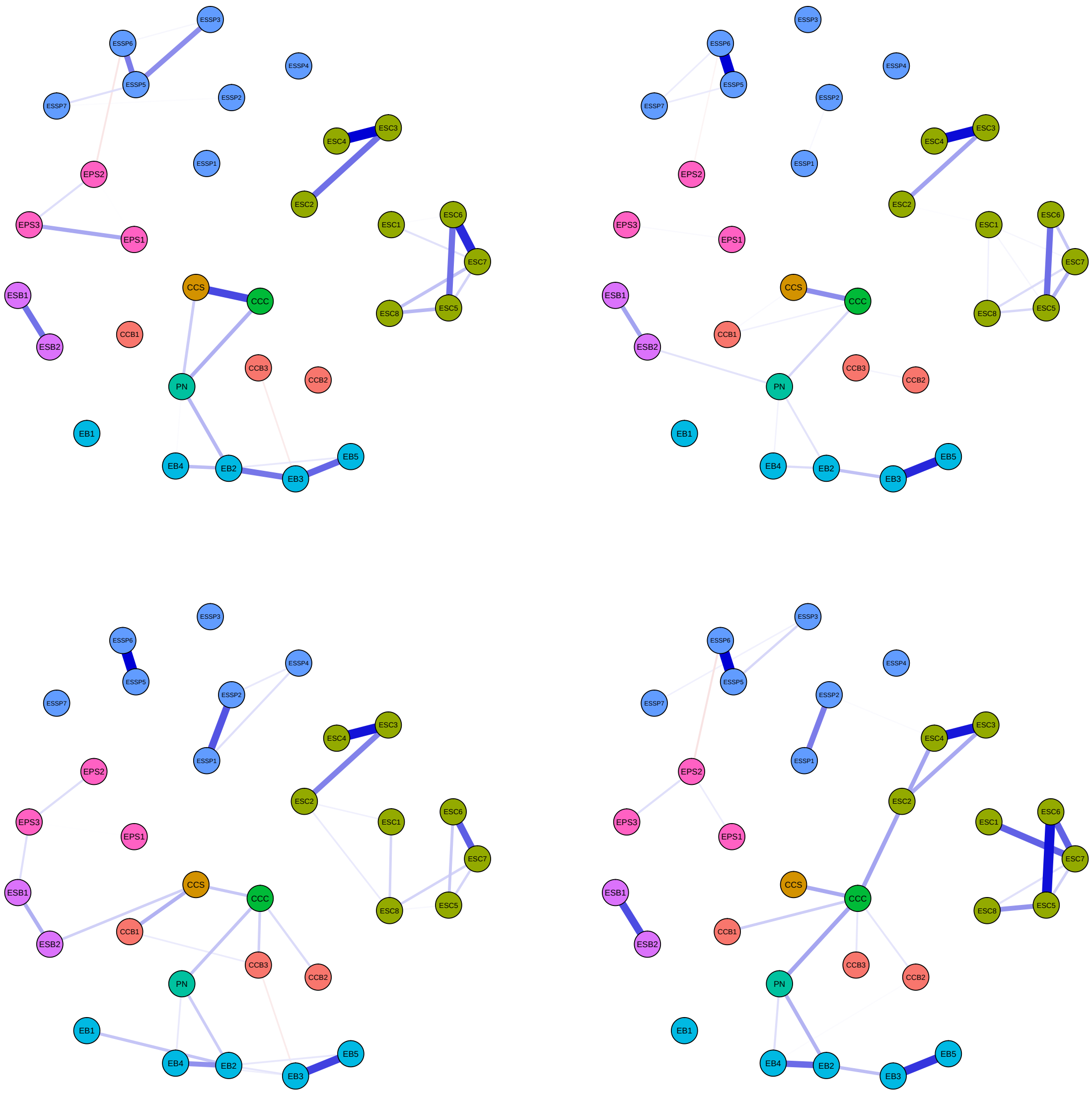

Figure 2. The estimated networks for Ireland (top-left); Sweden (top-right); Austria (bottom-left); and the Netherlands (bottom-right). Nodes are color-coded by rubric concept. A thicker edge corresponds to a larger regularized partial correlation. Blue edges reflect positive relationships and red edges reflect negative relationships.

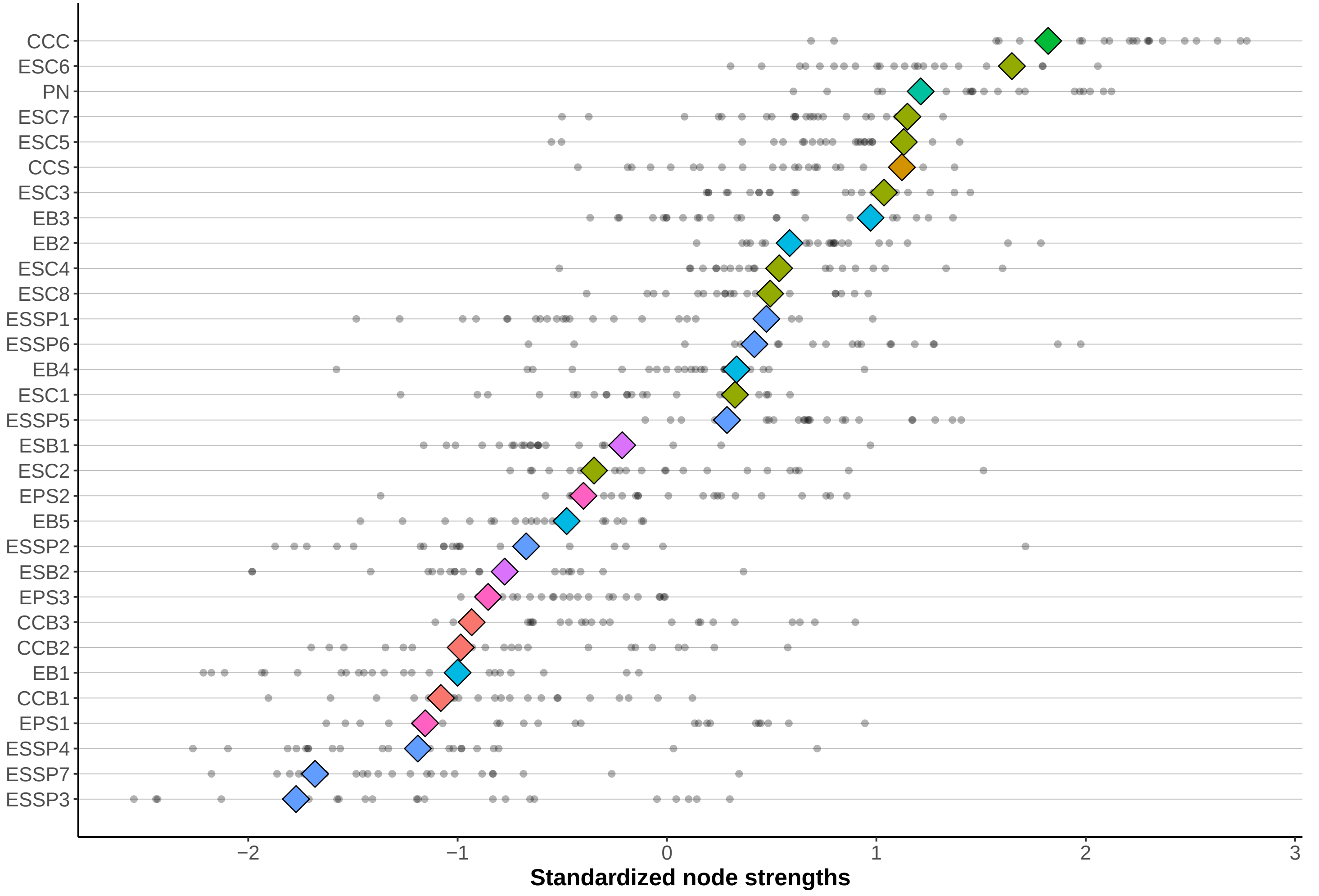

Figure 3. The overall node strengths, corresponding to the node strengths in the overall network, are displayed in the diamonds. These diamonds are color-coded by rubric concept, using the same color scheme as the network visualization in Figure 1. The circles correspond to the standardized node strengths per country.

To investigate country differences in network structures, we performed a k-means cluster analysis on the network models for the 23 individual countries. The gap statistics (Tibshirani et al., 2001) for various cluster sizes are reported on osf.io/85mah. The gap statistic is lower for a two-cluster solution than for a one-cluster solution, which means that a two-cluster solution explained less variance than a one-cluster solution. Thus, the gap statistics for the cluster analyses revealed that a one-cluster solution best fits the data. This suggests that networks are very similar across the 23 countries.

To test the robustness of our approach, we performed additional cluster analyses using 4 different methods and another evaluation criterium, the within sum of squares. The results of the pam, clara, and hcut clustering algorithms also suggest a one-cluster solution fits the data best because the gap statistic is lower for a two-cluster solution than for a one-cluster solution. The visualizations for the within sum of squares corresponding to the k-means, pam, clara, and hcut clustering algorithms suggests that a single-cluster solution as the solution that best fit the data, because the line that indicates the within sum of squares was diagonal and did not have a steep drop or sharp cut. Yet, the visualization for the within sum of squares corresponding to the fuzzy algorithm seemed to suggest that a two-cluster solution would fit the data best, with one cluster mainly including north-west-European countries and one cluster mainly including south-east-European countries. In total, nine of the ten cluster analyses yielded that a single-cluster solution would fit the data best, which suggests that the results of these cluster analyses are robust.

4. Discussion

The present paper had two aims. First, we wanted to investigate the relationships between the variables in the environmental module of ESS8 via network analyses, in particular relationships between climate beliefs, efficacy beliefs, energy security beliefs, energy preferences, and energy behavior. In doing so, we also explored which variables are most central in this data set. Second, we wanted to investigate the extent to which the networks are similar across the 23 countries included in the dataset.

We first estimated the overall network model to explore regularized partial correlations between the variables. We noticed particularly strong relationships between preferences for either renewable or fossil energy sources. Specifically, participants tended to have consistent preferences for renewable energy sources, and consistent preferences for fossil energy sources, while preferences for renewable sources were hardly related to preferences for fossil energy sources. Contrary to the module's authors' expectations, we did not find a negative relationship between preferences for nuclear energy and renewable energy. In fact, a preference for nuclear energy was not related to preferences for any of the other energy sources. These findings have important theoretical implications, as they suggest people have no consistent preferences for energy sources: A preference for renewables is not associated with (dis)liking fossil fuels or nuclear energy. Future research is needed to understand why this is the case.

Interestingly, our results suggest that two types of energy security concerns can be distinguished. Specifically, we found strong positive relationships between concern about the affordability of energy and the dependency on fossil fuels and (fossil) energy imports. These items all reflect threats for energy security in the long term. Additionally, we found relatively strong positive relationships between concern about interruptions in energy supply because of natural disasters, insufficient power generation, technical failures, and terrorist attacks. These items all imply temporary threats to energy supply. Hence, it seems that participants differentiate between short and long term threats to energy security, which is an interesting finding both from a theoretical and practical point of view. Future research can study which factors affect both types of energy security concerns.

Most efficacy beliefs were positively related to each other. Specifically, the more participants think that large numbers of people are able to reduce climate change, the more they think that they themselves too are able to reduce climate change. Furthermore, the more participants think that large groups of people will limit their energy use, the more they think that the government will take action to reduce climate change. Yet, self-efficacy (i.e., the extent to which people think they can use less energy) was not related to the other types of efficacy beliefs. These findings suggest that beliefs on the likelihood and efficacy of actions of different actors to reduce climate change were positively related, while such beliefs are not related to the extent to which people think they are able to engage in the relevant actions. In other words, beliefs on the effectiveness of actions of different actors do not seem to be related to beliefs on whether one can engage in relevant actions, suggesting that it is theoretically relevant to clearly distinguish the various efficacy beliefs. Future research can examine which factors affect the different types of efficacy beliefs.

In line with the module's authors' expectations, the more people believe that climate change is caused by human actions, and the more they believe that climate change has negative impacts, the more they worry about climate change. This climate change worry is in turn positively related to thinking more about climate change and a higher sense of personal responsibility to reduce climate change. Feelings of personal responsibility were in turn positively related to the belief that limiting one's own energy use will reduce climate change. These findings are in line with common theories, notably the Value-Belief-Norm theory (VBN; Stern, 2000) and the Norm Activation Model (NAM; Schwartz, 1977), that suggest that stronger concern about climate problems is likely to increase the belief that reducing one's energy use would help mitigate climate change mitigation (personal outcome efficacy), which in turn is likely to strengthen the personal norm to act on climate change (Stern, 2000; van der Werff & Steg, 2015). Yet, in contrast to what would be expected on the basis of the VBN theory and the NAM, we found no relationships between personal norm and energy conservation behaviors or energy policy preferences when the other variables were controlled for. Relationships shown in the network may be weaker as they reflect partial correlations, controlling for many other variables not part of the VBN or the NAM. Follow-up research can explicitly test the VBN theory, the NAM, and other theories using only the relevant items from the ESS8 data. Additionally, experimental studies could test causal relationships between VBN and NAM variables.

Contrary to the module's authors' expectations, we did not find relationships between energy supply source preferences and any other variable in the model. We also find hardly any support for relationships between energy conservation behaviors and energy policy support, and most other variables in the model. We found that buying energy efficient appliances was related to support for a policy aimed at banning the least energy efficient appliances, which suggests that participants who are more likely to buy energy efficient appliances also are more likely to support policies that would promote the use of energy efficient appliances.

The most central variables in our models, i.e., the variables with the highest node strengths, were feelings of personal responsibility to reduce climate change (personal norm), and climate change concern. This means that, in our set of variables, these variables had the strongest statistical relationships with the other variables. This may be because these variables are both influenced by some variables in the module (e.g., salience of climate change, belief in the reality of climate change, and belief that climate change has a positive or negative impact affect climate change concern; Bostrom et al., 2012; Poortinga et al., 2011) and influence other variables in the module (e.g., climate change concern affect personal norm, which in turn affects efficacy beliefs), which we cannot test as we rely on correlational data. Future research is needed to test the causal relationships between the module variables.

We found that the relationships between the variables in the ESS are rather robust and similar across countries. First, visual inspection of the country networks revealed that the network structure is similar across countries. Second, the strong correlations between the node strengths per country with the node strength of the other countries suggest that the relationships between variables were similar across countries. Variables that were strongly related to other variables in the data set in one country also tend to be strongly related to other variables in other countries. Third, nine out of ten cluster analyses revealed that a one-cluster solution best summarized the country network models, suggesting that the network structure is very similar across countries. Taken together, these three analyses converged to the conclusion that the network structures in the different countries are comparable. This has theoretical implications for future cluster analyses on network models, as it thus may be the case that simpler clustering models are sufficient for network models. Future research is needed to test to what extent and when country differences in relationships between variables of interest are likely to occur.

Other research in cross-cultural settings usually points to some heterogeneity between countries. This may be because papers typically compare differences in mean scores across countries, rather than comparing whether relationships between variables are similar across countries. Indeed, some studies have suggested that relationships between items or variables are rather similar across countries (Groot & Steg, 2007). Similarly, a recent network analysis revealed that although mean scores on variables did vary across groups (in this case members and non-members of a sustainable energy initiative), relationships between variables were very similar across groups (Bhushan et al., 2019).

Our network analysis, which was applied to a theoretically grounded questionnaire, is predominantly exploratory in nature. As discussed above, our analyses revealed various interesting findings and theoretical implications that may guide researchers to further investigate relationships between variables included in the environmental module of the ESS8. This is particularly useful for investigating relationships between a wide range of variables that are typically not included in the same dataset, and for investigating integrated theoretical models. The large ESS data set is useful here, because it combines variables from different theoretical models that were, to our knowledge, not studied together before. Yet, because our findings are correlational, the causality of the relationships between variables is not clear.

We only analyzed data from the environmental module of ESS8 and not variables from the core module. Some of these variables, such as values (e.g., Schwartz, 1977; Stern, 2000), may be relevant to understand energy preferences. Future studies could examine relationships between different subsets of variables included in the ESS8. When adding extra variables to network models, researchers should carefully consider if these extra variables are meaningful. Network model edges reflect (regularized) partial correlations, and this 'partialness' reflects unique relationships between variables (i.e., when controlling for other variables). Every added variable may change the value of these edges, and more importantly the interpretation of these edges. Therefore, adding variables may be risky, or even detrimental to the results, when these variables are added or removed without proper rationale. Fortunately, edge weights typically barely change when adding or removing an unrelated or irrelevant variable to a network model, which implies that the risks of adding irrelevant variables may be less than the risks of missing relevant variables – especially because missing relevant variables may lead to spurious relationships.

Future research could employ a combination of different methods (most notably experiments) to investigate the strength of different relationships and in particular the causality of these relationships. Furthermore, in ESS8, variables were typically measured via single items, which may be less reliable than multi-item measures. Therefore, results should be interpreted with care. Finally, the ESS data set corresponds to 22 European countries and Israel. The question remains whether similar findings would be found in other countries, in particular non-European and developing countries. This is a question for future research.

4.2. Conclusion

We conducted a network analysis to explore relationships between climate change beliefs and environmental preferences, included in the environmental module in the ESS8. Our exploratory analysis showed positive relationships between climate change salience, climate change beliefs, climate change concern, personal outcome expectancy, and personal norm, which supports prominent theories such as the VBN and the NAM. Yet, in contrast to what would be expected based on the VBN and the

NAM, personal norm was not related to energy saving behavior and energy policy support when the other variables are controlled for. Beliefs on the efficacy of actions of different actors to reduce climate change were mostly positively related, but there were no relationships between beliefs of the efficacy of actions of different actors and beliefs on the extent to which participants are able to use less energy, suggesting that it is theoretically important to distinguish both types of efficacy. Participants had consistent preferences for fossil energy sources or renewable energy sources, respectively. A preference for nuclear power was hardly related to any of the other included variables. Results further suggest that two types of energy security concerns can be distinguished, reflecting temporary and long term threats to energy security, respectively. Energy supply source preferences, energy policy support, and energy conservation behaviors were hardly uniquely related to the other module variables. The relationships between variables in the network are highly similar across the 23 European countries, which implies that the networks are comparable across countries.

Acknowledgements

The authors would like to thank the Center for Information Technology of the University of Groningen for providing access to the Peregrine high performance computing cluster. The authors would like to thank Nitin Bhushan, Lieke Voncken, Anne van Valkengoed, and Maliheh Namazkhan for comments and helpful discussion. The European Social Survey (ESS) is a European Research Infrastructure Consortium (ERIC). Participating countries contribute to the central coordination costs of the ESS ERIC as well as covering the costs of their own fieldwork and national coordination.

Author contributions

MV performed the data analyses and led the writing of the article. CA provided help and feedback on the analyses. CA and LS provided detailed feedback on several versions of drafts of the article. WP and GB provided feedback on a first and the last versions of the draft of the article. WP, GB, and LS were part of the team that developed the environmental module in the ESS8. All authors approved the manuscript for submission. All authors provided input that helped accommodate reviewers' suggestions. MV led the revisions and extra analyses for resubmission of the paper. All authors approved the manuscript for resubmission.

Declaration of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Open data

The data is freely available on the website of the European Social Survey (http://www.europeansocialsurvey.org/data/download.html).

Open materials

All used R code is available on osf.io/85mah/.

Software used

All data handling was done in R (R Core Team, 2019) using RStudio (RStudio Team, 2019). For a list of used package and version numbers, we refer to osf.io/85mah/.

References

Bandura, A. (1994). *Self-efficacy.* New York: John Wiley & Sons.

Bhushan, N., Mohnert, F., Sloot, D., Jans, L., Albers, C., & Steg, L. (2019). Using a gaussian graphical model to explore relationships between items and variables in environmental psychology research. *Frontiers in Psychology*, *10*, 1050. doi: 10.3389/fpsyg.2019.01050

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, *9*, 91-121. doi: 10.1146/annurev-clinpsy-050212-185608

Bostrom, A., O'Connor, R. E., Böhm, G., Hanss, D., Bodi, O., Ekström, F., ... Sælensminde, I. (2012). Causal thinking and support for climate change policies: International survey findings. *Global Environmental Change*, *22*(1), 210 - 222. doi: 10.1016/j.gloenvcha.2011.09.012

Brandt, M. J., Sibley, C. G., & Osborne, D. (2019). What is central to political belief system networks? *Personality and Social Psychology Bulletin*, *45*(9), 1352-1364. doi: 10.1177/0146167218824354

Chen, J., & Chen, Z. (2009). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, *95*, 759-771. doi: 10.1093/biomet/asn034

Chester, L. (2010). Conceptualising energy security and making explicit its polysemic nature. *Energy Policu*, *38*, 887-895. doi: 10.1016/j.enpol.2009.10.039

Dalege, J., Borsboom, D., van Harreveld, F., van der 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. doi: 10.1037/a0039802

Dalege, J., Borsboom, D., van Harreveld, F., & van der Maas, H. L. J. (2019). A network perspective on attitude strength: Testing the connectivity hypothesis. *Social Psychological and Personality Science*, *10*(6), 746-756. doi: 10.1177/1948550618781062

Demski, C., Poortinga, W., & Pidgeon, N. (2014). Exploring public perceptions of energy security risks in the UK. *Energy Policy*, *66*, 369 - 378. doi: 10.1016/j.enpol.2013.10.079

Demski, C., Poortinga, W., Whitmarsh, L., Fisher, S., Steg, L., Umit, R., . . . Pohjolainen, P. (2018). National context is a key determinant of energy security concerns across Europe. *Nature Energy*, *3*, 882-888. doi: 10.1038/s41560-018-0235-8

Epskamp, S., Borsboom, D., & Fried, E. I. (2017). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*. doi: 10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012a). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*, 1-18. doi: 10.18637/jss.v048.104

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012b). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1–18.

Ernst, A. F., & Albers, C. J. (2017). Regression assumptions in clinical psychology research practice — a systematic review of common misconceptions. *PeerJ*. doi: 10.7717/peerj.3323

European Social Survey. (2016a). ESS Round 8: European Social Survey Round 8 Data

(2016). Data file edition 2.0. NSD - Norwegian Centre for Research Data, Norway – Data Archive and distributor of ESS data for ESS ERIC. [Computer software manual]. London: ESS ERIC Headquarters c/o City University London.

European Social Survey. (2016b). ESS Round 8 Module on Climate Change and Energy [Computer software manual]. London: ESS ERIC Headquarters c/o City University London.

Foygel, R., & Drton, M. (2010). Extended Bayesian Information Criteria for Gaussian Graphical Models. In J. D. Lafferty, C. K. I. Williams, J. Shawe-Taylor, R. S. Zemel, & A. Culotta (Eds.), *Advances in neural information processing systems 23* (pp. 604–612). Curran Associates, Inc.

Freeman, L. C. (1978). Centrality in social networks: Conceptual clarification. *Social Networks*, *1*, 215-239. doi: 10.1016/0378-8733(78)90021-7

Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., van Dijk, H. M. H., Bockting, C. L. H., … Karstoft, K.-I. (2018). Replicability and generalizability of posttraumatic stress disorder (ptsd) networks: A cross-cultural multisite study of ptsd symptoms in four trauma patient samples. *Clinical Psychological Science*, *6*(3), 335-351. doi: 10.1177/2167702617745092

Friedman, J. H., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, *9*, 432-441. doi: 10.1093/biostatistics/kxm045

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, *21*(11), 1129–1164. doi: 10.1002/spe.4380211102

Gardner, G. T., & Stern, P. C. (2002). *Environmental problems and human behavior.*

Boston, MA: Pearson Custom Publishing.

Groot, J. I. D., & Steg, L. (2007). Value orientations and environmental beliefs in five countries: Validity of an instrument to measure egoistic, altruistic and biospheric value orientations. *Journal of Cross-Cultural Psychology*, *38*(3), 318-332. doi: 10.1177/0022022107300278

IPCC. (2018). Summary for policymakers. In V. Masson-Delmotte et al. (Eds.), *Global warming of 1.5°c. an ipcc special report on the impacts of global warming of 1.5°c above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change.* Geneva, Switzerland: World Meteorological Organization.

Jones, P. J., Ma, R., & McNally, R. J. (2019). Bridge centrality: A network approach to understanding comorbidity. *Multivariate Behavioral Research.* doi: 10.1080/00273171.2019.1614898

Kassambara, A., & Mundt, F. (2017). factoextra: Extract and visualize the results of multivariate data analyses [Computer software manual]. Retrieved from `https://CRAN.R-project.org/package=factoextra` (R package version 1.0.5)

Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data.* New York: John Wiley & Sons.

Koletsou, A., & Mancy, R. (2011). Which efficacy constructs for large-scale social dilemma problems? individual and collective forms of efficacy and outcome expectancies in the context of climate change mitigation. *Risk Management*, *13*(4), 184–208. doi: 10.1057/rm.2011.12

Krone, T., Albers, C. J., Kuppens, P., & Timmerman, M. E. (2018). A multivariate statistical model for emotion dynamics. *Emotion*, *18*, 739 - 754. doi:

10.1037/emo0000384

Lauritzen, S. L. (1996). *Graphical models* (1st ed.). Oxford: Clarendon Press.

Lubell, M. (2002). Environmental activism as collective action. *Environment and Behavior*, *34*(4), 431-454. doi: 10.1177/00116502034004002

MacQueen, J. B. (1967). Some methods for classification and analysis of multivariate observations, proceedings of 5-th berkeley symposium on mathematical statistics and probability. *Berkeley, University of California Press*, *1*, 281-297.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., & Hornik, K. (2017). cluster: Cluster analysis basics and extensions [Computer software manual]. (R package version 2.0.6 — For new features, see the 'Changelog' file (in the package source))

Newman, M. (2010). *Networks: An introduction.* New York, NY, USA: Oxford University Press, Inc.

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, *32*, 245-251. doi: 10.1016/j.socnet.2010.03.006

Poortinga, W., Aoyagi, M., & Pidgeon, N. F. (2013). Public perceptions of climate change and energy futures before and after the fukushima accident: A comparison between britain and japan. *Energy Policy*, *62*, 1204 - 1211. doi: 10.1016/j.enpol.2013.08.015

Poortinga, W., Spence, A., Whitmarsh, L., Capstick, S., & Pidgeon, N. F. (2011). Uncertain climate: An investigation into public scepticism about anthropogenic climate change. *Global Environmental Change*, *21*(3), 1015-1024. (Symposium on Social Theory and the Environment in the New World (dis)Order) doi: https://doi.org/10.1016/j.gloenvcha.2011.03.001

Poortinga, W., Whitmarsh, L., Steg, L., Böhm, G., & Fisher, S. (2019). Climate change perceptions and their individual-level determinants: A cross-european analysis. *Global Environmental Change*, *55*, 25 - 35. doi: https://doi.org/10.1016/j.gloenvcha.2019.01.007

R Core Team. (2019). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria.

Rahmstorf, S. (2004). *The climate sceptics.*

RStudio Team. (2019). RStudio: Integrated Development Environment for R [Computer software manual]. Boston, MA.

Schwartz, S. H. (1977). Normative influences on altruism. In L. Berkowitz (Ed.), (Vol. 10, p. 221 - 279). Academic Press. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0065260108603585` doi: 10.1016/S0065-2601(08)60358-5

Simpson, E. H. (1951). The interpretation of interaction in contingency tables. *Journal of the Royal Statistical Society, Series B*, *13*, 238 - 241.

Steg, L., & De Groot, J. I. M. (2010). Explaining prosocial intentions: Testing causal relationships in the norm activation model. *British Journal of Social Psychology*, *49*, 725-743. doi: 10.1348/014466609X477745

Steg, L., De Groot, J. I. M., Drijerink, L., Abrahamse, W., & Siero, F. (2011). General antecedents of environmental behavior: Relationships between values, worldviews, environmental concern, and environmental behavior. *Society and Natural Resources*, *24*, 309-317. doi: 10.1080/08941920903214116

Stern, P. C. (2000). Toward coherent theory of environmentally significant behavior. *Journal of Social Issues*, *56*, 407-424. doi: 10.1111/0022-4537.00175

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, *58*, 267-288. doi: 10.2307/2346178

Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistic Society*, *63*, 411 - 423. doi: 10.2307/2680607

van der Werff, E., & Steg, L. (2015). One model to predict them all: Predicting energy behaviours with the norm activation model. *Energy Research & Social Science*, *6*, 8 - 14. doi: https://doi.org/10.1016/j.erss.2014.11.002

Weir, T. (2018). Renewable energy in the pacific islands: Its role and status. *Renewable and Sustainable Energy Reviews*, *94*, 762 - 771. doi: 10.1016/j.rser.2018.05.069

Williams, M. N., Grajales, C. A. G., & Kurkiewicz, D. (2013). Assumptions of multiple regression: Correcting two misconceptions. *Practical Assessment, Research & Evaluation*, *18*, 1-14.