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

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Abstract

11
12 Understanding public attitudes to climate change and energy preferences is key to a
13 successful transformation to a low-carbon society. While many studies have examined
14 relationships between specific variables, little is known about the breadth of
15 relationships between multiple climate and energy-relevant concepts. In this paper we
16 used network models to explore and visualize relationships between climate change
17 beliefs and energy preferences, using data from Round 8 of the European Social Survey
18 (ESS8). ESS8 was conducted in 22 European countries and Israel. We found positive
19 relationships between climate change salience, climate change beliefs, climate change
20 concern, personal norm, and personal outcome expectancy, in line with prominent
21 theories within the area. Moreover, beliefs on efficacy of actions of different actors (i.e.,
22 governments, large groups of people) to reduce climate change were positively related,
23 and participants had consistent preferences for fossil energy sources or renewable energy
24 sources, respectively. Furthermore, two types of energy security concerns could be
25 distinguished, reflecting temporary and long term threats to energy security,
26 respectively. Energy supply source preferences, energy policy support, and energy
27 conservation behaviors were mostly not uniquely related to the other module variables.
28 Furthermore, the relationships between variables, reflected in the network structure,
29 were comparable across countries.

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

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

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

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

56 an overview of the variables and their full wording).

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

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

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

89 Following the collective action model framework (Lubell, 2002), the model
90 included five types of efficacy beliefs reflecting personal efficacy, collective efficacy, and
91 institutional efficacy beliefs. Specifically, the module included the belief that one is able
92 to use less energy (self-efficacy), the belief that limiting one's own energy use will help
93 reduce climate change (personal outcome expectancy), the belief that large number of
94 people will limit their energy use to reduce climate change (collective efficacy), the
95 belief that governments limit energy use to reduce climate change (institutional
96 efficacy), and the belief that collective action by large numbers of people will reduce
97 climate change (collective outcome efficacy; cf. Bandura, 1994; Koletsou & Mancy,
98 2011; Lubell, 2002; Steg & De Groot, 2010). We aimed to explore how these efficacy
99 beliefs would be related, and to what extent each of these efficacy beliefs would be
100 related to energy preferences. Moreover, we aimed to explore whether people have
101 consistent preferences for energy supply sources, including fossil energy, renewable, and
102 nuclear energy sources. For example, a strong preference for renewables may be
103 associated with a weak preference for fossil energy sources.

104 As yet, researchers typically investigate small parts of the ESS8. Indeed,
105 several studies investigate relationships between a subset of variables included in the
106 environmental and core modules in the ESS8, such as socio-political¹ and demographic¹
107 predictors of climate change beliefs (Poortinga et al., 2019), or relationships between
108 variables from the environmental module and country-level variables, such as
109 relationships between country characteristics¹ and energy security concerns (Demski et
110 al., 2018).

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

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

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

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

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

151 in new theorizing, that can be tested in follow-up research.

152 There are various ways to investigate whether certain constructs are related.

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

166 Psychological network models were first introduced in the field of
167 psychopathology (e.g., Borsboom & Cramer, 2013; Fried et al., 2018). Network models
168 have been successfully employed to explore relationships between various concepts (e.g.,
169 beliefs, attitudes, anxiety and depression symptoms) in various subfields of psychology,
170 including social psychology (Brandt, Sibley, & Osborne, 2019; Dalege et al., 2016;
171 Dalege, Borsboom, van Harreveld, & van der Maas, 2019), clinical psychology (Fried et
172 al., 2018), and environmental psychology (Bhushan et al., 2019). These papers, like
173 ours, aimed to investigate relationships between variables of interest, to further develop
174 theorizing in their fields. For instance, network analyses in psychopathology revealed

175 that multiple disorders often have common symptoms. Symptoms that appear to be the
176 link between two disorders are termed bridge nodes (e.g., Jones, Ma, & McNally, 2019).
177 By specifically intervening on these bridge nodes in treatment, one minimizes the risk of
178 comorbidity, that is the risk that the presence of one disorder is causing the occurrence of
179 the second disorder through these common symptoms. Thus, by studying the network
180 one developed new theory to intervene in patients with certain disorders. Similarly,
181 network analyses on the items included in the environmental module of ESS8 can result
182 in new theorizing.

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

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

197 An advantage of network models is that they allow for investigating
198 relationships between a wide range of variables that are derived from multiple, yet

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

209 Network models are well-suited to reveal which variables play a central role in
210 the network, which implies that they are related to many other variables or strongly
211 related to a few other variables. To investigate this concept of centrality, we investigate
212 the node strength centrality measure (Freeman, 1978; Opsahl, Agneessens, & Skvoretz,
213 2010). A larger node strength corresponds to a more central variable. However, it is
214 important that researchers keep theory and/or common sense in mind when
215 investigating centrality, as a relatively non-central variable may still be important
216 (Fried et al., 2018). For example, belief in the reality of climate change may not be a
217 central variable in terms of node strength centrality because it is only related to the
218 salience of climate change, but it may be relevant for the network as it may be
219 indirectly related to many other variables through climate change salience.

220 We further aim to test how stable the resulting network is. Specifically, we will
221 test network stability by examining whether the network remains similar when a large
222 number of data points have been removed at random from the analyses. A highly stable

223 network remains similar to itself when removing a large number of participants from the
224 analysis, which implies that the resulting network is robust.

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

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

247 which the relationships between variables as reflected in the networks are similar across
248 countries.

249 **2. Method**

250 **2.1. Participants and procedure**

251 Round 8 of the European Social Survey (ESS8) was conducted between
252 August 2016 and December 2017, with data collection in the 23 individual countries
253 usually taking place within a three-month period. Next to the core module that is
254 administered every 2 years, ESS8 contained an environmental module: A dedicated
255 module on climate change beliefs, energy security beliefs, and energy preferences.
256 Interviews were conducted face-to-face in participants' own homes with people aged 15
257 years and over. The data set included 44,387 participants (47.4 % men, 52.6 % women,
258 and 9 participants did not disclose their gender). The mean age of the participants was
259 49.14 years (range = 15-100, SD = 18.61). The full questionnaire and the European
260 Social Survey Round 8 dataset can be downloaded from
261 <http://www.europeansocialsurvey.org> (European Social Survey, 2016a). Detailed
262 information about the data collection, including coding and software used in the
263 different countries, can be found in the ESS8 Data Documentation Report (European
264 Social Survey, 2016b). The unweighted descriptive statistics for the variables included
265 in the environmental module for the individual countries are reported in Table 2².

²The weighted descriptive statistics are reported in Demski et al. (2018). The weighted descriptive 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 %

266 **2.2. Variables**

267 The environmental module in ESS8 covered nine different rubric concepts³,
268 namely (1) climate change beliefs, (2) climate change salience, (3) climate change
269 concern, (4) energy security concerns, (5) personal norm, (6) efficacy beliefs, (7) energy
270 supply source preferences, (8) energy saving behaviors, and (9) energy policy support.
271 Table 1 shows the variables included and the exact questionnaire wording for all
272 included items, as well as the rubric concepts and short descriptions that we use
273 throughout this paper.

274 **2.3. Data analyses**

275 **2.3.1. Missing data.** Analyses were performed with pairwise deletion of
276 missing data. Unusable responses for any reason (e.g., due to survey flow, an answer
277 outside the possible range, refusing to answer, or not knowing an answer) were treated
278 as missing data. These missing data may not be Missing Completely At Random.
279 Participants (n = 1,327; 3 % of the total sample) who indicated that they believed that
280 climate change is not real did not rate a number of items, namely climate change cause
281 (CCB2), climate change impact (CCB3), climate change concern (CCC), personal
282 responsibility to reduce climate change (PN), the likelihood that limiting one's own
283 energy use will help reduce climate change (EB2), the likelihood that large numbers of
284 people will limit their energy use (EB3), the likelihood that climate change would
285 reduce if large numbers of people would limit their energy use (EB4), and the likelihood
286 that governments in enough countries will take actions to reduce climate change (EB5).

³We 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.

287 **2.3.2. Standardizing data.** To prevent the possibility of country
288 differences in means driving the overall network model and distorting the correlations
289 (i.e., Simpson’s paradox; Simpson, 1951), we standardized the data by rescaling all
290 variables such that for each country every variable had a mean of 0 and a standard
291 deviation of 1. Indeed, the unstandardized network (available on osf.io/85mah) shows
292 some spurious negative correlations due to these differences in mean levels.

293 **2.3.3. Network analyses.** For all our analyses, we used unweighted data.
294 We followed the common strategy of using Mixed Graphical Models (i.e., a type of
295 network model suitable for variables measured on different scales) to visualize
296 relationships between variables included in the ESS8 module (MGMs; Epskamp,
297 Borsboom, & Fried, 2017; Lauritzen, 1996). Not all of our variables, for instance those
298 with only a few answer possibilities (see Table 1 for an overview of the number of
299 answer possibilities), can be assumed to be normally distributed. Some of our variables
300 are treated as non-normally distributed because they have 7 or fewer answer
301 possibilities. The `qgraph` (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom,
302 2012a) and `bootnet` (Epskamp et al., 2017) packages take this into account by
303 computing correlations suited for ordinal variables (e.g., polychoric and polyserial
304 correlations). Furthermore, inferences for correlations are known to be robust against
305 violations of the normality assumption (Ernst & Albers, 2017; Williams, Grajales, &
306 Kurkiewicz, 2013). Therefore, data transformations were not necessary. To prevent a
307 large network model showing many small partial correlations that are relatively weak,
308 we used a technique called regularization that forces small partial correlations to zero
309 (Chen & Chen, 2009; Foygel & Drton, 2010; Friedman, Hastie, & Tibshirani, 2008;

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

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

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

⁵We 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.

331 **2.3.4. Centrality.** In order to examine which variables are more strongly
332 related to other variables (i.e., more central in the network), we computed the node
333 strength centrality measures (node strength henceforth) that reflects the sum of the
334 absolute values of all the (regularized) partial correlation coefficients (i.e., all edges)
335 that a variable has. We used the R package bootnet (Epskamp et al., 2017) to compute
336 the node strength of each variable (Freeman, 1978; Newman, 2010; Opsahl et al., 2010).
337 We used node strength as our measure of centrality because this measure is generally
338 the most stable and intuitively clear centrality measure (Epskamp et al., 2017). Node
339 strength is not easily interpreted without context. For instance, for country X, the node
340 strength of node Y was Z. Whether Z is large or small depends on many factors,
341 including the sample size and the node strengths of the other nodes in the network. In
342 order to facilitate cross-country comparison, we therefore standardized the node
343 strengths. A standardized node strength of 0 implies an average strength. Negative
344 standardized node strengths imply that the corresponding variables are, compared to
345 the other variables in the network, less strongly than average related to the other
346 variables. Positive standardized node strengths correspond to variables that are more
347 strongly than average related to the other variables in the network⁶. To investigate
348 network stability, we investigated whether node strengths change when random data
349 were removed from the analyses. In a stable network, the node strengths and the
350 ordering of variables based on node strength should not change much.

351 **2.3.5. Country comparison.** To examine whether the network structure is
352 similar across countries, and thus whether the relationships between variables are

⁶In 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.

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

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

377 et al., 2001). For the exact implementation of these algorithms in the factoextra
378 package, we refer to Kassambara and Mundt (2017a).

379 To test the robustness of our findings from the k-means cluster analyses, we
380 also employed four other clustering techniques from the R package cluster (Maechler,
381 Rousseeuw, Struyf, Hubert, & Hornik, 2017): the partitioning around medoids method,
382 the clustering large applications method, the fuzzy analysis method, and the hierarchical
383 clustering and cut the three method. The first three methods are used by the cluster
384 package in R, and statistical details are described in (Kaufman & Rousseeuw, 1990,
385 Chapter 2-4). The hcut-method is from the R package factoextra (Kassambara &
386 Mundt, 2017). For all five methods, we initially used the gap statistic to decide upon
387 the number of clusters. To further explore robustness of our results, we also evaluated
388 the models with another criterium, namely the within sum of squares. The results of all
389 10 (5 algorithms \times 2 evaluation methods) are visualized using the factoextra package
390 (Kassambara & Mundt, 2017). All code and results are included on osf.io/85mah.

391

3. Results

392 3.1. Network analyses

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

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

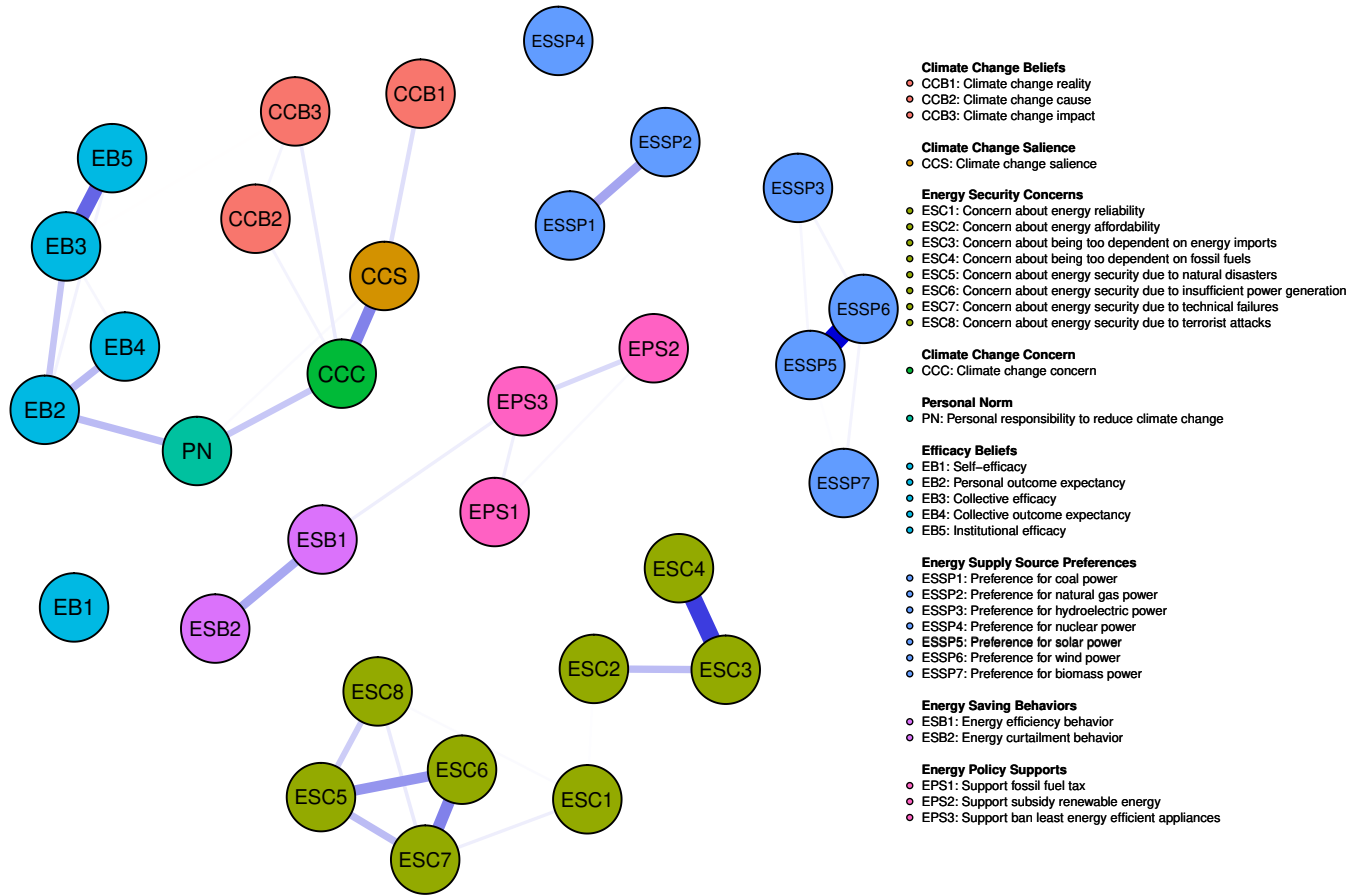


Figure 1. The estimated network for the full data set. Nodes are color-coded by rubric concept. A thicker edge corresponds to a larger regularized partial correlation. Blue edges reflect positive relationships and red edges reflect negative relationships.

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

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

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

429 **3.1.1. Centrality.** Figure 3 shows the standardized node strengths per
430 variable (diamonds). Climate change concern (CCC) was the variable with the highest
431 centrality score, and was related in particular to climate change salience (CCS). Climate
432 change concern had weak relationships with feelings of personal responsibility to reduce
433 climate change (PN), the belief that climate change is anthropogenic (CCB2), and the
434 belief that climate change has negative consequences (CCB3). Personal responsibility to
435 reduce climate change (PN) was the variable with the second highest node strength.
436 The more people feel responsible to mitigate climate (PN), the more they have thought
437 about climate change (CCS), and the more they think individual actions will be
438 effective to mitigate climate change (EB5). The least central variables in the network
439 were a preference for hydroelectric power (ESSP3) and a preference for biomass power
440 (ESSP7). Both of these variables had no substantial relationships with any of the other
441 variables.

442 **3.1.2. Network stability.** Stability analyses revealed that the overall
443 network was stable. On osf.io/85mah, we illustrate the node strengths for the overall
444 network and what happens to those when random data rows (i.e., data from randomly
445 selected individuals) were removed from the analyses. As in Figure 3, the most central
446 variables remain climate change concern (CCC) and personal responsibility to reduce
447 climate change (PN). The node strengths of these variables decreased slightly as more
448 data were removed from the analyses. The order of node strengths remains relatively
449 stable too, which means that the node strengths have been estimated accurately and
450 that the network is very stable.

451 **3.2. Country comparison**

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

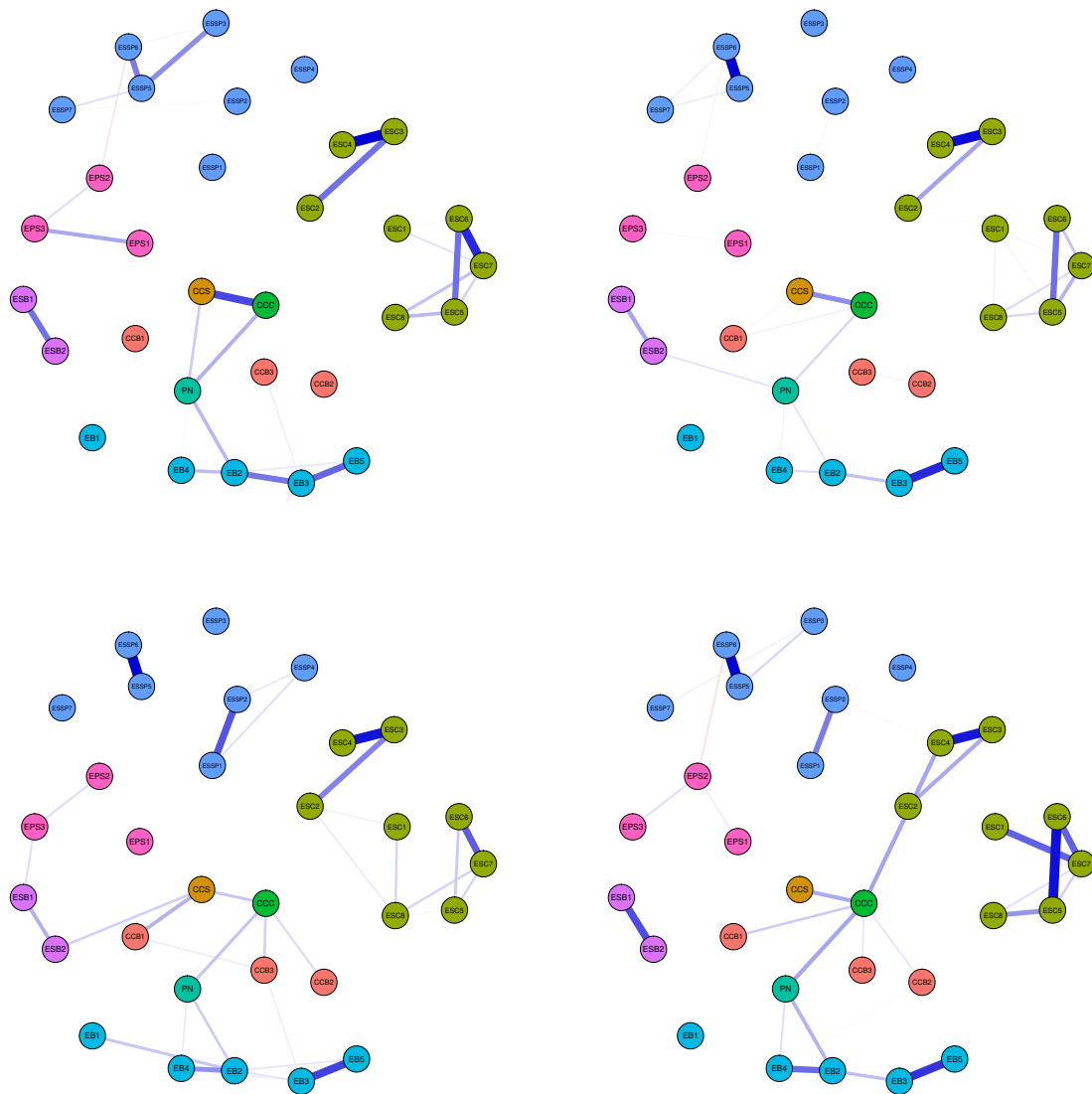


Figure 2. The estimated networks for Ireland (top-left); Sweden (top-right); Austria (bottom-left); and the Netherlands (bottom-right). Nodes are color-coded by rubric concept. A thicker edge corresponds to a larger regularized partial correlation. Blue edges reflect positive relationships and red edges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

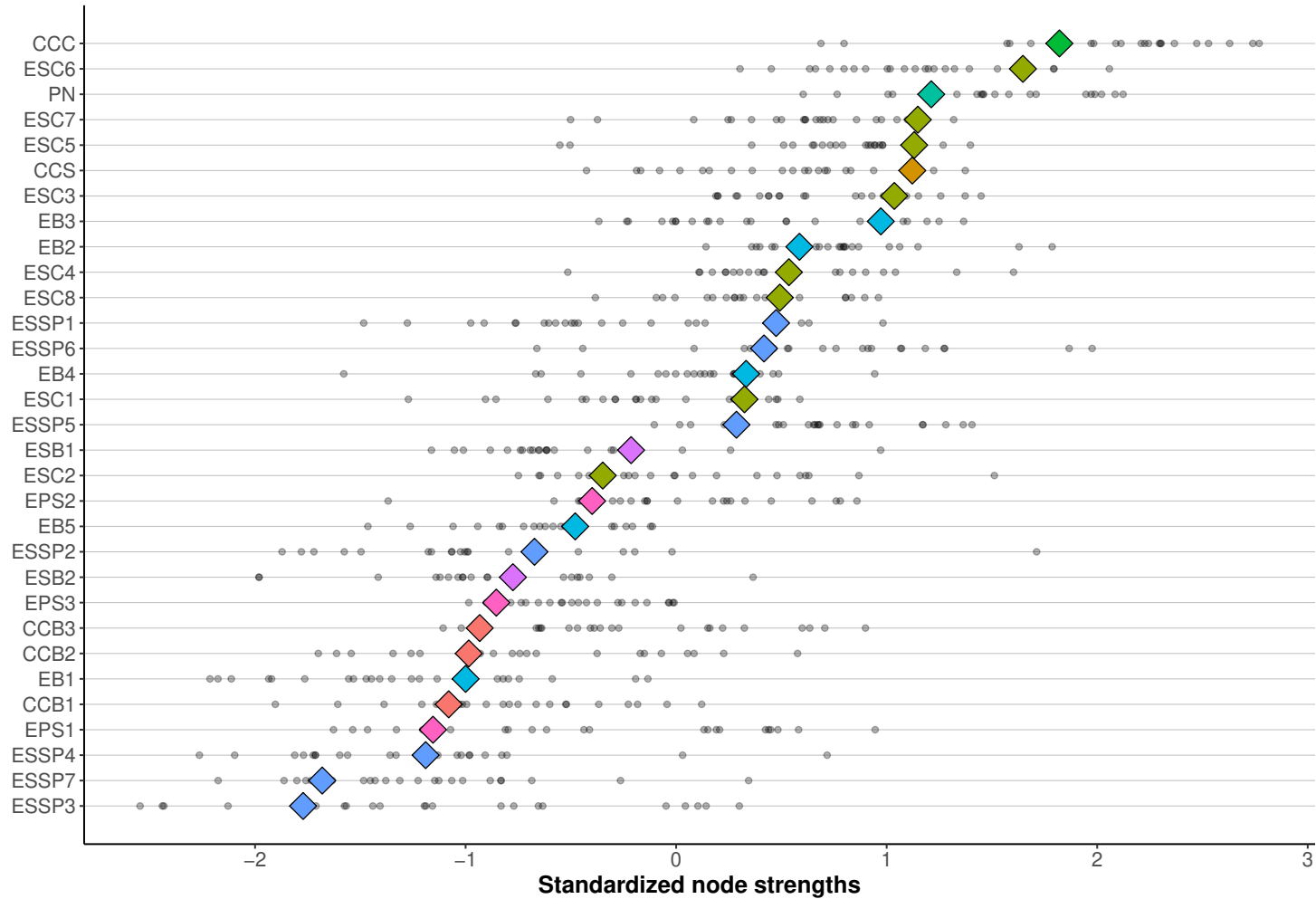


Figure 3. The overall node strengths, corresponding to the node strengths in the overall network, are displayed in the diamonds. These diamonds are color-coded by rubric concept, using the same color scheme as the network visualization in Figure 1. The circles correspond to the standardized node strengths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

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

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

484 **4. Discussion**

485 The present paper had two aims. First, we wanted to investigate the
486 relationships between the variables in the environmental module of ESS8 via network

487 analyses, in particular relationships between climate beliefs, efficacy beliefs, energy
488 security beliefs, energy preferences, and energy behavior. In doing so, we also explored
489 which variables are most central in this data set. Second, we wanted to investigate the
490 extent to which the networks are similar across the 23 countries included in the dataset.

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

503 Interestingly, our results suggest that two types of energy security concerns
504 can be distinguished. Specifically, we found strong positive relationships between
505 concern about the affordability of energy and the dependency on fossil fuels and (fossil)
506 energy imports. These items all reflect threats for energy security in the long term.
507 Additionally, we found relatively strong positive relationships between concern about
508 interruptions in energy supply because of natural disasters, insufficient power
509 generation, technical failures, and terrorist attacks. These items all imply temporary
510 threats to energy supply. Hence, it seems that participants differentiate between short

511 and long term threats to energy security, which is an interesting finding both from a
512 theoretical and practical point of view. Future research can study which factors affect
513 both types of energy security concerns.

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

528 In line with the module's authors' expectations, the more people believe that
529 climate change is caused by human actions, and the more they believe that climate
530 change has negative impacts, the more they worry about climate change. This climate
531 change worry is in turn positively related to thinking more about climate change and a
532 higher sense of personal responsibility to reduce climate change. Feelings of personal
533 responsibility were in turn positively related to the belief that limiting one's own energy
534 use will reduce climate change. These findings are in line with common theories,

535 notably the Value-Belief-Norm theory (VBN; Stern, 2000) and the Norm Activation
536 Model (NAM; Schwartz, 1977), that suggest that stronger concern about climate
537 problems is likely to increase the belief that reducing one's energy use would help
538 mitigate climate change mitigation (personal outcome efficacy), which in turn is likely
539 to strengthen the personal norm to act on climate change (Stern, 2000; van der Werff &
540 Steg, 2015). Yet, in contrast to what would be expected on the basis of the VBN theory
541 and the NAM, we found no relationships between personal norm and energy
542 conservation behaviors or energy policy preferences when the other variables were
543 controlled for. Relationships shown in the network may be weaker as they reflect partial
544 correlations, controlling for many other variables not part of the VBN or the NAM.
545 Follow-up research can explicitly test the VBN theory, the NAM, and other theories
546 using only the relevant items from the ESS8 data. Additionally, experimental studies
547 could test causal relationships between VBN and NAM variables.

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

556 The most central variables in our models, i.e., the variables with the highest
557 node strengths, were feelings of personal responsibility to reduce climate change
558 (personal norm), and climate change concern. This means that, in our set of variables,

559 these variables had the strongest statistical relationships with the other variables. This
560 may be because these variables are both influenced by some variables in the module
561 (e.g., salience of climate change, belief in the reality of climate change, and belief that
562 climate change has a positive or negative impact affect climate change concern;
563 Bostrom et al., 2012; Poortinga et al., 2011) and influence other variables in the module
564 (e.g., climate change concern affect personal norm, which in turn affects efficacy
565 beliefs), which we cannot test as we rely on correlational data. Future research is
566 needed to test the causal relationships between the module variables.

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

582 Other research in cross-cultural settings usually points to some heterogeneity

583 between countries. This may be because papers typically compare differences in mean
584 scores across countries, rather than comparing whether relationships between variables
585 are similar across countries. Indeed, some studies have suggested that relationships
586 between items or variables are rather similar across countries (Groot & Steg, 2007).
587 Similarly, a recent network analysis revealed that although mean scores on variables did
588 vary across groups (in this case members and non-members of a sustainable energy
589 initiative), relationships between variables were very similar across groups (Bhushan et
590 al., 2019).

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

601 We only analyzed data from the environmental module of ESS8 and not
602 variables from the core module. Some of these variables, such as values (e.g., Schwartz,
603 1977; Stern, 2000), may be relevant to understand energy preferences. Future studies
604 could examine relationships between different subsets of variables included in the ESS8.
605 When adding extra variables to network models, researchers should carefully consider if
606 these extra variables are meaningful. Network model edges reflect (regularized) partial

607 correlations, and this 'partialness' reflects unique relationships between variables (i.e.,
608 when controlling for other variables). Every added variable may change the value of
609 these edges, and more importantly the interpretation of these edges. Therefore, adding
610 variables may be risky, or even detrimental to the results, when these variables are
611 added or removed without proper rationale. Fortunately, edge weights typically barely
612 change when adding or removing an unrelated or irrelevant variable to a network model,
613 which implies that the risks of adding irrelevant variables may be less than the risks of
614 missing relevant variables – especially because missing relevant variables may lead to
615 spurious relationships.

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

624 **4.2. Conclusion**

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

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

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652 ERIC as well as covering the costs of their own fieldwork and national coordination.

Author contributions

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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

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

Open data

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

Open materials

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

Software used

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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

673

- 674 Bandura, A. (1994). *Self-efficacy*. New York: John Wiley & Sons.
- 675 Bhushan, N., Mohnert, F., Sloot, D., Jans, L., Albers, C., & Steg, L. (2019). Using a
676 gaussian graphical model to explore relationships between items and variables in
677 environmental psychology research. *Frontiers in Psychology, 10*, 1050. doi:
678 10.3389/fpsyg.2019.01050
- 679 Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach
680 to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*,
681 91-121. doi: 10.1146/annurev-clinpsy-050212-185608
- 682 Bostrom, A., O'Connor, R. E., Böhm, G., Hanss, D., Bodi, O., Ekström, F., ...
683 Sælensminde, I. (2012). Causal thinking and support for climate change policies:
684 International survey findings. *Global Environmental Change, 22*(1), 210 - 222.
685 doi: 10.1016/j.gloenvcha.2011.09.012
- 686 Brandt, M. J., Sibley, C. G., & Osborne, D. (2019). What is central to political belief
687 system networks? *Personality and Social Psychology Bulletin, 45*(9), 1352-1364.
688 doi: 10.1177/0146167218824354
- 689 Chen, J., & Chen, Z. (2009). Extended Bayesian information criteria for model selection
690 with large model spaces. *Biometrika, 95*, 759-771. doi: 10.1093/biomet/asn034
- 691 Chester, L. (2010). Conceptualising energy security and making explicit its polysemic
692 nature. *Energy Policu, 38*, 887-895. doi: 10.1016/j.enpol.2009.10.039
- 693 Dalege, J., Borsboom, D., van Harreveld, F., van der Berg, H., Conner, M., & van der
694 Maas, H. L. J. (2016). Toward a formalized account of attitudes: The causal
695 attitude network (can) model. *Psychological Review, 123*, 2-22. doi:
696 10.1037/a0039802

- 697 Dalege, J., Borsboom, D., van Harreveld, F., & van der Maas, H. L. J. (2019). A
698 network perspective on attitude strength: Testing the connectivity hypothesis.
699 *Social Psychological and Personality Science*, *10*(6), 746-756. doi:
700 10.1177/1948550618781062
- 701 Demski, C., Poortinga, W., & Pidgeon, N. (2014). Exploring public perceptions of
702 energy security risks in the UK. *Energy Policy*, *66*, 369 - 378. doi:
703 10.1016/j.enpol.2013.10.079
- 704 Demski, C., Poortinga, W., Whitmarsh, L., Fisher, S., Steg, L., Umit, R., ...
705 Pohjolainen, P. (2018). National context is a key determinant of energy security
706 concerns across Europe. *Nature Energy*, *3*, 882-888. doi:
707 10.1038/s41560-018-0235-8
- 708 Epskamp, S., Borsboom, D., & Fried, E. I. (2017). Estimating psychological networks
709 and their accuracy: A tutorial paper. *Behavior Research Methods*. doi:
710 10.3758/s13428-017-0862-1
- 711 Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D.
712 (2012a). qgraph: Network visualizations of relationships in psychometric data.
713 *Journal of Statistical Software*, *48*, 1-18. doi: 10.18637/jss.v048.104
- 714 Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D.
715 (2012b). qgraph: Network visualizations of relationships in psychometric data.
716 *Journal of Statistical Software*, *48*(4), 1-18.
- 717 Ernst, A. F., & Albers, C. J. (2017). Regression assumptions in clinical psychology
718 research practice — a systematic review of common misconceptions. *PeerJ*. doi:
719 10.7717/peerj.3323
- 720 European Social Survey. (2016a). ESS Round 8: European Social Survey Round 8 Data

- 721 (2016). Data file edition 2.0. NSD - Norwegian Centre for Research Data, Norway
 722 – Data Archive and distributor of ESS data for ESS ERIC. [Computer software
 723 manual]. London: ESS ERIC Headquarters c/o City University London.
- 724 European Social Survey. (2016b). ESS Round 8 Module on Climate Change and
 725 Energy [Computer software manual]. London: ESS ERIC Headquarters c/o City
 726 University London.
- 727 Foygel, R., & Drton, M. (2010). Extended Bayesian Information Criteria for Gaussian
 728 Graphical Models. In J. D. Lafferty, C. K. I. Williams, J. Shawe-Taylor,
 729 R. S. Zemel, & A. Culotta (Eds.), *Advances in neural information processing*
 730 *systems 23* (pp. 604–612). Curran Associates, Inc.
- 731 Freeman, L. C. (1978). Centrality in social networks: Conceptual clarification. *Social*
 732 *Networks*, 1, 215-239. doi: 10.1016/0378-8733(78)90021-7
- 733 Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., van Dijk, H. M. H., Bockting,
 734 C. L. H., ... Karstoft, K.-I. (2018). Replicability and generalizability of
 735 posttraumatic stress disorder (ptsd) networks: A cross-cultural multisite study of
 736 ptsd symptoms in four trauma patient samples. *Clinical Psychological Science*,
 737 6(3), 335-351. doi: 10.1177/2167702617745092
- 738 Friedman, J. H., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance
 739 estimation with the graphical lasso. *Biostatistics*, 9, 432-441. doi:
 740 10.1093/biostatistics/kxm045
- 741 Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed
 742 placement. *Software: Practice and Experience*, 21(11), 1129–1164. doi:
 743 10.1002/spe.4380211102
- 744 Gardner, G. T., & Stern, P. C. (2002). *Environmental problems and human behavior*.

- 745 Boston, MA: Pearson Custom Publishing.
- 746 Groot, J. I. D., & Steg, L. (2007). Value orientations and environmental beliefs in five
747 countries: Validity of an instrument to measure egoistic, altruistic and biospheric
748 value orientations. *Journal of Cross-Cultural Psychology*, *38*(3), 318-332. doi:
749 10.1177/0022022107300278
- 750 IPCC. (2018). Summary for policymakers. In V. Masson-Delmotte et al. (Eds.), *Global*
751 *warming of 1.5°C. an ipcc special report on the impacts of global warming of 1.5°C*
752 *above pre-industrial levels and related global greenhouse gas emission pathways, in*
753 *the context of strengthening the global response to the threat of climate change.*
754 Geneva, Switzerland: World Meteorological Organization.
- 755 Jones, P. J., Ma, R., & McNally, R. J. (2019). Bridge centrality: A network approach
756 to understanding comorbidity. *Multivariate Behavioral Research*. doi:
757 10.1080/00273171.2019.1614898
- 758 Kassambara, A., & Mundt, F. (2017). factoextra: Extract and visualize the results of
759 multivariate data analyses [Computer software manual]. Retrieved from
760 <https://CRAN.R-project.org/package=factoextra> (R package version 1.0.5)
- 761 Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data*. New York: John
762 Wiley & Sons.
- 763 Koletsou, A., & Mancy, R. (2011). Which efficacy constructs for large-scale social
764 dilemma problems? individual and collective forms of efficacy and outcome
765 expectancies in the context of climate change mitigation. *Risk Management*,
766 *13*(4), 184–208. doi: 10.1057/rm.2011.12
- 767 Krone, T., Albers, C. J., Kuppens, P., & Timmerman, M. E. (2018). A multivariate
768 statistical model for emotion dynamics. *Emotion*, *18*, 739 - 754. doi:

- 769 10.1037/emo0000384
- 770 Lauritzen, S. L. (1996). *Graphical models* (1st ed.). Oxford: Clarendon Press.
- 771 Lubell, M. (2002). Environmental activism as collective action. *Environment and*
772 *Behavior*, 34(4), 431-454. doi: 10.1177/00116502034004002
- 773 MacQueen, J. B. (1967). Some methods for classification and analysis of multivariate
774 observations, proceedings of 5-th berkeley symposium on mathematical statistics
775 and probability. *Berkeley, University of California Press*, 1, 281-297.
- 776 Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., & Hornik, K. (2017). cluster:
777 Cluster analysis basics and extensions [Computer software manual]. (R package
778 version 2.0.6 — For new features, see the 'Changelog' file (in the package source))
- 779 Newman, M. (2010). *Networks: An introduction*. New York, NY, USA: Oxford
780 University Press, Inc.
- 781 Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted
782 networks: Generalizing degree and shortest paths. *Social Networks*, 32, 245-251.
783 doi: 10.1016/j.socnet.2010.03.006
- 784 Poortinga, W., Aoyagi, M., & Pidgeon, N. F. (2013). Public perceptions of climate
785 change and energy futures before and after the fukushima accident: A comparison
786 between britain and japan. *Energy Policy*, 62, 1204 - 1211. doi:
787 10.1016/j.enpol.2013.08.015
- 788 Poortinga, W., Spence, A., Whitmarsh, L., Capstick, S., & Pidgeon, N. F. (2011).
789 Uncertain climate: An investigation into public scepticism about anthropogenic
790 climate change. *Global Environmental Change*, 21(3), 1015-1024. (Symposium on
791 Social Theory and the Environment in the New World (dis)Order) doi:
792 <https://doi.org/10.1016/j.gloenvcha.2011.03.001>

- 793 Poortinga, W., Whitmarsh, L., Steg, L., Böhm, G., & Fisher, S. (2019). Climate change
794 perceptions and their individual-level determinants: A cross-european analysis.
795 *Global Environmental Change, 55*, 25 - 35. doi:
796 <https://doi.org/10.1016/j.gloenvcha.2019.01.007>
- 797 R Core Team. (2019). R: A language and environment for statistical computing
798 [Computer software manual]. Vienna, Austria.
- 799 Rahmstorf, S. (2004). *The climate sceptics*.
- 800 RStudio Team. (2019). RStudio: Integrated Development Environment for R
801 [Computer software manual]. Boston, MA.
- 802 Schwartz, S. H. (1977). Normative influences on altruism. In L. Berkowitz (Ed.),
803 (Vol. 10, p. 221 - 279). Academic Press. Retrieved from
804 <http://www.sciencedirect.com/science/article/pii/S0065260108603585>
805 doi: 10.1016/S0065-2601(08)60358-5
- 806 Simpson, E. H. (1951). The interpretation of interaction in contingency tables. *Journal*
807 *of the Royal Statistical Society, Series B, 13*, 238 - 241.
- 808 Steg, L., & De Groot, J. I. M. (2010). Explaining prosocial intentions: Testing causal
809 relationships in the norm activation model. *British Journal of Social Psychology,*
810 *49*, 725-743. doi: 10.1348/014466609X477745
- 811 Steg, L., De Groot, J. I. M., Drijerink, L., Abrahamse, W., & Siero, F. (2011). General
812 antecedents of environmental behavior: Relationships between values, worldviews,
813 environmental concern, and environmental behavior. *Society and Natural*
814 *Resources, 24*, 309-317. doi: 10.1080/08941920903214116
- 815 Stern, P. C. (2000). Toward coherent theory of environmentally significant behavior.
816 *Journal of Social Issues, 56*, 407-424. doi: 10.1111/0022-4537.00175

- 817 Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the*
818 *Royal Statistical Society. Series B (Methodological)*, 58, 267-288. doi:
819 10.2307/2346178
- 820 Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in
821 a data set via the gap statistic. *Journal of the Royal Statistic Society*, 63, 411 -
822 423. doi: 10.2307/2680607
- 823 van der Werff, E., & Steg, L. (2015). One model to predict them all: Predicting energy
824 behaviours with the norm activation model. *Energy Research & Social Science*, 6,
825 8 - 14. doi: <https://doi.org/10.1016/j.erss.2014.11.002>
- 826 Weir, T. (2018). Renewable energy in the pacific islands: Its role and status. *Renewable*
827 *and Sustainable Energy Reviews*, 94, 762 - 771. doi: 10.1016/j.rser.2018.05.069
- 828 Williams, M. N., Grajales, C. A. G., & Kurkiewicz, D. (2013). Assumptions of multiple
829 regression: Correcting two misconceptions. *Practical Assessment, Research &*
830 *Evaluation*, 18, 1-14.