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1 **The use of systems models to identify food waste drivers**

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Abstract

In developed countries, the largest share of food waste is produced at household level. Most studies on consumers' food waste use models that identify covariates as significant when in fact they may not be, particularly where these models use many variables. Here, using EU-level Eurobarometer data from 2013, we use alternative analytical methods that avoid these problems (Bayesian Networks) to identify the impact of household characteristics and other variables on self-assessed food waste. Our analysis confirmed that the country, the age of the respondent, the status (student/non-student), and a belief that the family wastes too much are related to the level of self-assessed food waste. But we found no evidence that waste behaviours differ between people living in urban and rural areas, and little support of a difference between genders. Households from lower-income EU countries (e.g. Portugal, Greece, Bulgaria, Cyprus and Latvia), as well as students and young adults tend to report higher levels of food waste. Hence, the adoption of an EU strategy based on the concept of subsidiarity, and of country-level policy measures targeting different age groups is suggested. Furthermore, our analysis shows that policy makers need to be wary of relying on analysis based on large datasets that do not control for false-positives, particularly when sample sizes are small.

Keywords

Consumers, decision modelling, household food waste, European Union

21 **1. Introduction**

22 Food waste represents a major challenge for responsible business and consumer behaviours,
23 and for sustainable food value chains (FAO 2011; FAO 2013). For this reason, the Sustainable
24 Development Goal 12, Target 12.3 calls for halving per capita food waste and reducing food
25 losses by 2030 (UNEP 2016). Also the EU has made the reduction of food waste a priority
26 (European Commission 2015). The waste produced at household level is thought to be
27 responsible for the largest proportion of all food wasted in developed countries (Parfitt et al.
28 2010). Stenmarck et al. (2016) estimated food waste in the 28 EU countries (extrapolated from
29 data for 11 countries) at 87.6 ± 13.7 (95% CI) million tonnes, with 46.5 ± 4.4 (95% CI) million
30 tonnes coming from households. This means that between 46.7 and 63.5% of the total EU food
31 waste comes from households.

32

33 Food waste occurring at household level has multiple and interrelated drivers, with
34 heterogeneous geographical and social impacts (Wenlock & Buss 1977; Sonesson et al. 2005;
35 Barr 2007; Koivupuro et al. 2012; Canali et al. 2014; Parizeau et al. 2015; Stancu et al. 2016;
36 Setti et al. 2016). Hence, the identification and the design of effective policy interventions
37 requires the comprehension of this complexity using a systems approach (Godfray et al. 2010).

38

39 The current approaches for identifying the drivers of food waste to design targeted policy
40 interventions generally rely on frequentist statistics (i.e. null hypothesis testing) (e.g. Quested
41 & Luzecka 2014; Secondi et al. 2015). However, null hypothesis testing does not provide the
42 probability of the null hypothesis or of its alternative; hence, its usefulness to underpin decision
43 making is limited (Claxton 1997; Kileen 2005). In addition, the utility or “value” of a decision
44 or intervention cannot be estimated or identified using null hypothesis testing (Claxton 1997).
45 Assessments of food waste drivers using a regression framework often test multiple
46 explanatory variables (Secondi et al. 2015, Stancu et al. 2016; Visschers et al. 2016). However,
47 with an increased number of variables, the probability of Type I errors (i.e. false positives)
48 increases. This, in combination with the problem of selective reporting and “researcher degrees
49 of freedom” (i.e., the incomplete publication of the outcomes measured, or of the analyses
50 performed; Simons et al. 2011; Reid et al. 2015; see Figure 5), which affects all scientific fields,
51 implies that the actual drivers of household food waste cannot be reliably identified.

52

53 This represents a challenge for policy makers who may wish to use scientific papers as evidence
54 to underpin robust policy decisions. Decision-analytic approaches may offer greater assistance

55 to policy makers in situations where potential interventions are beset by complexity (Stewart
56 et al. 2014). The processes of making decisions in the face of complexity and uncertainty have
57 long been of academic interest; Bernoulli (in the 1700s) and Laplace (in the 1800s) addressed
58 utility and probability in reference to decision making (Howard 2007). These theoretical
59 applications of decision theory were robustly applied to the real world during the Second World
60 War (which led to the development of the modern language associated with systems models)
61 (Howard 2007). More recently, policy interventions in fields as diverse as public health (e.g.
62 Nutt et al. 2010), sustainable energy (e.g. Wang et al. 2009) and natural resource management
63 (e.g. Punt and Hilborn 1997) have been explored using decision analysis.

64

65 Differently from null-hypothesis testing, decision-theoretic approaches look at a problem in a
66 systemic way, addressing the net changes in the outcome (i.e. the variable) of interest, rather
67 than arbitrary levels of statistical significance (i.e. there is no test of statistical significance).
68 Importantly, decision-theoretic approaches explicitly (and mathematically) incorporate
69 uncertainty, which highly characterizes the data used to underpin the decisions on addressing
70 food waste.

71

72 Secondi et al. (2015) used data from the Eurobarometer Flash survey (388) “Attitudes of
73 Europeans to waste management and resource efficiency” (European Commission 2014) to
74 identify the variables affecting food waste through a regression model (i.e. using frequentist
75 statistics). Here, a similar but unique subset of the Eurobarometer dataset is used to identify
76 the drivers of self-reported EU food waste, but it is analysed by means of a decision-theoretic
77 approach. The reporting of the variable selection and statistical procedures in Secondi et al.
78 (2015) were insufficient to replicate their study in full to allow a direct comparison of the two
79 approaches. However, we demonstrate the potential for Type I error in a frequentist regression
80 framework that does not account for model structural uncertainty. Our overarching goal is to
81 highlight potential realms of interventions, and indicate which of them might help reduce food
82 waste. As food waste is a complex issue, with many interrelated variables potentially affecting
83 it, a systems model is used to assess it as a system in a probabilistic framework.

84

85 **2. Material and methods**

86 *2.1 Dataset*

87 The open-source Eurobarometer dataset is used. This dataset presents three main advantages:
88 1) it represents the largest survey on consumer attitudes to food waste in terms of sample size

89 and geographical extent; 2) it registers the attitudes to food waste within the whole EU, thus
90 capturing inter-country heterogeneity; 3) it represents a valid informative basis to support
91 policy interventions under subsidiary schemes.

92

93 Eurobarometer Flash surveys were carried out through *ad hoc* thematic telephone interviews
94 run at the request of the European Commission. The interviews used to build the dataset
95 occurred in December 2013. Overall, 26,595 households were asked 20 questions on their
96 attitudes and behaviours in relation to household food waste. Respondents were asked to
97 estimate the amount of food purchased that goes to waste (see Table 1 for the categories).
98 Additionally, demographic variables such as age, gender, nationality, age at which full-time
99 education stopped, current occupation, location (urban, rural, etc.), phone ownership, and
100 household composition (members aged 15 or over) were registered (for full details of the
101 survey, see http://ec.europa.eu/public_opinion/flash/fl_388_en.pdf accessed November 11,
102 2016).

103

104 An important caveat throughout the discussion that follows concerns the subjective nature of
105 the food waste measure considered. Although diary studies, and waste sorting or weighting
106 analysis could also be used to quantify household food waste, questionnaires are the most
107 common method due to their lower cost in terms of time and resources, even if their reliability
108 is questionable (Van Herpen et al. 2016; Høj 2012; Ventour 2008). Indeed, when asked to
109 quantify their own food waste, consumers tend to rely on judgment heuristics, such as
110 availability (i.e. using the first piece of information coming to their mind, e.g. the last time they
111 threw away food), and to be affected by systematic biases such as positive illusion, or social
112 desirability, that lead to underestimation (Giordano 2016). Furthermore, when asked a
113 percentage, like in the Eurobarometer survey, consumers need to make a double computation,
114 which is subject to a frequency bias (Giordano 2016). These shortcomings may also be due to
115 the fact that the Eurobarometer survey was carried out before the best practices to measure
116 household food waste were systematically identified in Europe (Van Herpen et al. 2016).
117 However, to date, it remains the only (and the largest) study at EU level that policy makers can
118 use to design interventions against food waste.

119

120 *2.2 Systems model*

121 Fourteen variables were selected for the systems analysis (see Table 1), excluding those that
122 did not potentially relate to household food waste or household socio-economic status (among

123 others, the questions on whether the respondent thinks that an efficient resource use is related
124 to employment opportunities and economic growth at country level were also excluded).

125

126 To detect the drivers of self-reported food waste, thus developing a candidate network of food
127 waste in the EU, a machine-learned Bayesian Network (BN) was developed. BNs are graphical
128 representations of a network of variables (whereby related variables are joined by an arc, or
129 arrow), and of a set of conditional probabilities (where the state of a variable is conditional on
130 the states of n others) (Böttcher & Dethlefsen, 2003). BNs can incorporate empirical data along
131 with expert opinions. Full Bayesian hierarchical models allow more complete propagation of
132 uncertainty than BNs, but BNs are less computationally complex and are, thus, much more
133 transparent to stakeholders (Spiegelhalter et al., 2004; Bujkiewicz et al. 2011). Uncertainty in
134 BNs is handled through sensitivity analysis.

135

136 To develop the BN, the hill-climbing algorithm was used (this algorithm is included in the
137 “bnlearn” package of the statistical software R; Scutari & Denis 2014). This is an iterative
138 algorithm which provides an arbitrary solution of a complex problem, then tries to find a better
139 solution in terms of score (e.g., the Bayesian Information Criterion) by changing a single
140 element of the initial solution; if the score improves, the process is repeated starting with the
141 new solution, and so on.

142

143 *2.3 Sensitivity analysis & scenario setting*

144 Following the standard BN methodology, a one-way sensitivity analysis and scenario setting
145 was used to assess and interrogate the BN (Pitchforth & Mengersen 2013). First, the state of
146 one node (i.e. variable) at a time was changed, and the resulting probability of the food waste
147 node (i.e. the level of self-assessed food waste) was recorded. The next section of the paper
148 focuses on the self-reported food waste levels of “5% or less” and “50% or more”, since these
149 are likely to be the most relevant to policy makers. The focus on the level “50% or more”
150 allows the identification of the socio-economic and demographic characteristics of households
151 with highest self-reported waste to be targeted by means of policies. The focus on the
152 households who report “5% or less” allows the appreciation of the differences between the least
153 and the most (self-reported) wasters. Thus, the food waste node was set either at “5% or less”
154 or at “50% or more”, and the probabilities of each state in all the other nodes (i.e. the
155 probabilities that the household presents certain characteristics given one of these two levels
156 of self-assessed food waste, respectively) were recorded. Finally, a two-way sensitivity analysis

157 was carried out, changing the state of two nodes at each step, and recording the resulting state
158 of the food waste node.

159

160 *2.4 Type I errors in regression models*

161 Secondi et al. (2015) do not provide sufficient information to fully replicate their full model
162 structure. For example, there is no indication of how they addressed missing data in the Number
163 of Ecolabel licenses, in the Eurobarometer data, and how they partitioned Question 7 (“It would
164 convince me to separate (at least some) more of my waste”), a question with three more
165 categories than those reported by them.

166

167 Secondi et al. (2015) use a binomial model (0 where the percentage of food wasted is greater
168 than 5% of the food purchased; 1 if this percentage is 5% or less) with two levels (individual
169 and country level variables). They do not account for model structural uncertainty in their
170 assessment. In order to demonstrate the probability of Type I errors, we used their published
171 list of variables (Table 4 in Secondi et al. 2015) to build a candidate set of binomial general
172 linear models (GLMs). We only used the individual level variables, to reduce model complexity
173 and processing time. We used the Akaike Information Criterion corrected for small sample size
174 (AICc) to determine a set of the top 100 plausible (most parsimonious) model structures
175 (Burnham & Anderson 2002). For each of these models, we extracted the p-value and plotted
176 the distribution to illustrate the potential for Type I errors. GLMs, and model selection were
177 carried out using the “glmulti” package (Calcagno 2015) in the R programme.

178

179 **3. Results**

180 *3.1 Systems model*

181 The structure of the systems model is reported in Figure 1. The country and the age of the
182 respondent, as well as a self-reported belief that the family wastes too much lead to the largest
183 variation (i.e. there is a large amount of uncertainty associated with these nodes) in the food
184 waste node (Figure 2). The level of education has also a strong impact on self-reported food
185 waste.

186

187 The age of the respondent causes the largest variation in the probability of wasting “50% or
188 more”, followed by country of residence, while for the probability of wasting “5% or less” the
189 positions are reversed. The third largest variation is due to the level of education, followed by
190 the belief of wasting too much, the size of the household, and the occupational status. Gender

191 has a limited impact, and only on the probability of wasting “5% or less” of one’s purchased
192 food. It is worth noting that much more than half of the respondents declared to waste “5% or
193 less” of their food, while less than 1% declared wasting “50% or more” of their food.

194 There are considerable country-level differences in self-reported food waste (Figure 3). The
195 majority of respondents in all countries reported “5% or less” of the food purchased going to
196 waste; in Estonia and Lithuania, over 20% reported to waste “none” of it. The shares of
197 respondents reporting higher levels of waste, as well as those reporting “none” show much
198 more variability among countries, compared to the answer “5% or less”. Portugal, Greece,
199 Bulgaria, Cyprus, Latvia and Romania have the highest percentage of respondents reporting
200 that they discard “50% or more” of their food. Estonia, Lithuania, Malta and, again Romania
201 and Latvia have the highest percentage of respondents reporting that they waste “none” of their
202 food. Interestingly, all countries where over 10% of the respondents declared to waste “none”
203 of their food (apart from Malta) are post-communist countries that joined the EU in 2004 or
204 later.

205
206 Figure 4 shows the state of the most influential nodes given a specific state of the food waste
207 node (either “5% or less”, or “50% or more”). The age of the respondent has a strong impact
208 on self-assessed food waste: as this variable increases, the probability of wasting “5% or less”
209 of one’s purchased food increases steadily, while the probability of wasting “50% or more”
210 decreases, although less steadily (Figure 4). A similar pattern can be detected through two-way
211 sensitivity analysis, by limiting food waste to “50% or more”, and the countries to Greece,
212 Latvia and Cyprus. These three countries were hit particularly hard by the financial crisis and
213 the austerity measures that followed.

214
215 The level of education does not appear to have a strong impact on self-reported food waste;
216 however, compared to the others, the respondents who were “still studying” show a higher
217 probability of reporting “50% or more”, and a lower probability of reporting “5% or less” food
218 waste. As for the household size, it is an important variable when looking at the probability of
219 wasting “50% or more”: the families of three or more members show a greater probability of
220 reporting that they waste a high share of food. Large amounts of self-declared food waste are
221 also more likely to be observed in neighbourhoods with “a lot” or “quite a lot” of litter, and
222 among employees and self-employees. In contrast, households of one person, respondents
223 living in cleaner neighbourhoods, and unemployed respondents are more likely to waste “5%

224 or less” of their food compared to other groups. Finally, the amount of self-declared food waste
225 is strongly positively associated with the belief that the family is wasting too much, confirming
226 the role of one’s perception in driving self-reported food waste levels.

227

228 *3.2 Type I errors in regression models*

229 The binomial models with individual level variables and no interaction terms had a potential
230 of 134,217,728 different model structures. We took the top 100 models, and plotted the
231 distribution of the p-values for each variable (Supplementary Figure S1). Broadly, the results
232 of this analysis of the binomial regression models agree with the systems model. For example,
233 the age of the respondents and the response to question 4(2) (“I think my household is
234 generating too much waste”) were consistently statistically significant ($p < 0.05$). There was no
235 support for differences between rural and urban locations (i.e. we assume that statistically
236 significant findings relating to these variables would have a high probability of being Type I
237 errors).

238

239 **4. Discussion**

240 Using a systems approach to analyse the phenomenon of household food waste in the EU, we
241 have shown that the country and the age of the respondent, as well as the fact of being a student,
242 and a belief that the family wastes too much are key drivers of self-assessed food waste. It is
243 important to reiterate that, being self-reported, the level of waste can be potentially biased
244 (Ventour 2008). This remains an important – and method-independent – caveat throughout the
245 discussion that follows. However, the fact that the belief of wasting too much is related to the
246 probability of reporting a level of food waste of “50% or more” suggests that respondents are
247 aware, to an extent, of their waste levels.

248

249 Our findings deviate in several key aspects from those of Secondi et al. (2015), who adopt a
250 structured binomial regression approach to assess another subset of variables from the same
251 dataset. These authors identified a difference in the food waste behaviour between people living
252 in towns or cities, and those living in rural areas, with the former wasting more food. In
253 contrast, the BN shows that there is very little effect of the place of residence on the level of
254 self-reported food waste. Furthermore, Secondi et al. (2015) ascertain as statistically significant
255 the gender of the respondent, suggesting that women waste less food than men. The BN finds
256 very limited support for this. The reasons for these differences are related, among others, to the
257 fact that decision analysis methods do not rely on arbitrary measures (i.e. levels) of statistical

258 significance to assess the effects of variables, being thus robust to false-positives (Type I
259 errors). Additionally, using a multinomial approach further avoids over-estimating the
260 differences in these variables.

261

262 Secondi et al. (2015) show that education is significantly positively related with food waste
263 generation: the more the number of years spent in education, the larger the amount of self-
264 declared food waste. They relate this pattern either to the higher income of more educated
265 people, that allows them to waste more, or to the inability of less educated people to correctly
266 estimate their food waste. The BN does not support this finding; however, it shows that students
267 are more likely to waste “50% or more”, and less likely to waste “5% or less” of the food they
268 purchase, compared to other groups. This may be related to the financial pressure that may
269 affect students regardless of their country, causing them to purchase lower quality or perishable
270 food, or to their irregular food provisioning practices and eating behaviours, that prevent
271 consistent planning.

272

273 Age was identified as an important determinant of food waste, in line with Secondi et al. (2015)
274 and many others (e.g. Wassermann & Schneider 2005; IGD 2007; Glanz 2008; Koivupuro et
275 al. 2012; Quested & Luzecka 2014; Parizeau et al. 2015). We confirm this results with our
276 system approach. The older the respondent, the smaller the probability of reporting high levels
277 of food waste. Younger people should, thus, be one of the main targets of policy interventions
278 to reduce food waste.

279

280 Household size is considered a significant driver of food waste in many studies (Wenlock &
281 Buss 1977; Wassermann & Schneider 2005; IGD 2007; Barr 2007; Glanz 2008; Koivupuro et
282 al 2012; Quested & Luzecka 2014; Parizeau et al. 2015). The BN analysis confirms this finding:
283 larger households have a greater probability of reporting higher levels of food waste, although
284 it should be pointed out that the Eurobarometer survey measures household size differently
285 from other studies (i.e., only family members aged 15 or more years are considered).

286

287 Secondi et al. (2015) identify richer EU countries as potential targets of policy interventions to
288 reduce food waste, because they find that their citizens tend to waste more (i.e., they have a
289 higher probability of declaring to waste more than 5% of their food). Nevertheless, the results
290 of the BN suggest that respondents from poorer counties (i.e. Portugal, Greece, Bulgaria,
291 Cyprus, Latvia and Romania) have a higher probability of declaring to waste “50% or more”

292 of their food, and should thus be a focus of related policy intervention and awareness
293 campaigns. There are several competing explanations for this apparent contradiction with the
294 findings of Secondi et al. (2015), the first is analytical and the others sociological. Secondi et
295 al. (2015) use a binomial model with the data split from the original 7 categories of food waste
296 down to only two levels (less than 5 % or greater than 5 %), this split means that there may be
297 still more people wasting 5% to 50% in richer countries, while in poorer countries there are
298 relatively more people wasting “none” or “50% or more”. The fact that some EU countries,
299 most of which from Eastern Europe (Estonia, Lithuania, Malta, Romania, Latvia, Hungary,
300 Slovakia, Poland and Bulgaria), have also a higher share of respondents reporting no food
301 waste at all suggests that there may be different understandings of what constitutes food waste
302 in different countries. For example, food leftovers used to feed animals tend not to be
303 considered waste in some EU Member States (Parfitt et al. 2010). Indeed, respondents were not
304 provided a definition of food waste during the survey (European Commission 2014).
305 Furthermore, in Bulgaria, Hungary, Latvia and Romania (the four poorest EU countries by
306 GDP (PPP) per capita; IMF 2013) the share of respondents declaring to waste “none” of their
307 food and the share of those declaring to waste “50% or more” are both above the average. The
308 poor countries whose respondents have a higher probability of declaring to waste “50% or
309 more” of their food are all characterised by a low level of post-materialist self-expression
310 values and, thus, by a low environmental awareness (Inglehart & Baker 2000). Hence,
311 compared to rich countries, the respondents who have enough resources to waste food are less
312 likely to be affected by social desirability bias, and more likely to declare that they waste much
313 food. On the other hand, there should be a larger share of the population acting virtuously out
314 of necessity. This suggests that poverty and, especially, high levels of income inequality, may
315 generate a larger polarization in declared food waste behaviours.

316
317 Within each country, different age groups show different food waste behaviour. For example,
318 in Portugal, middle-age consumers (aged 35 to 44) are the most likely to report “50% or more”
319 food waste. Instead, in Latvia, Greece and Cyprus, the most likely to produce such high level
320 of waste are the respondents aged 15 to 34, and in Bulgaria, those aged 25 to 44. Overall,
321 elderly households tend to waste less.

322
323 Country-level policies to address food waste have been developing at different rates across the
324 EU. When the Eurobarometer survey was carried out in 2013, food waste was already the object
325 of national communication campaigns and of targeted national policies in some, mostly

326 industrialized, EU member States, namely Austria, Denmark, France, Germany, Italy, the
327 Netherlands, and the United Kingdom (BCFN 2012; Monier et al. 2011; Secondi et al. 2015).
328 However, in most of the countries that had joined the EU either in 2004 (Estonia, Latvia,
329 Lithuania, Cyprus, and Malta) or in 2007 (Romania and Bulgaria), food waste was neither the
330 objective of targeted communication campaigns, nor considered by national policies. In
331 addition, no uniform definition of food waste was available at EU level in 2013 (Östergren et
332 al. 2014). Different countries had different definitions, while quantification was rather weak,
333 and limited mainly to the estimates by Monier et al. (2011) and FAO (2011). This lack of
334 knowledge (especially in some countries) might have influenced the outcome of the survey even
335 more than cultural differences (See
336 http://ec.europa.eu/environment/archives/eussd/pdf/bio_foodwaste_report.pdf; accessed
337 October 18, 2016).

338

339 An important caveat in our comparisons to Secondi et al. (2015) is that we were unable to
340 replicate their model because not all information we needed to do so was available in the
341 publication (perhaps due to space constraints). This is a common problem hindering the
342 replication of scientific analyses, and does not (routinely, at least) indicate nefarious practices
343 (Gellman & Loken 2013). Researcher degrees of freedom (Simmons et al. 2011), and the (often
344 hidden) decisions that researchers take in data collection and analysis increase the probability
345 of Type I errors. In order to carry out an analysis, researchers must make a myriad of decisions
346 on which variables to measure, how much data to collect, how to dichotomise or transform
347 variables, etc. Figure 5 attempts to estimate the cumulative number of different decisions that
348 one would have to take in order to analyse the Eurobarometer data in relation to food waste.
349 Decisions made at each stage could fundamentally change the nature of the inference one
350 makes from the data.

351

352 **5. Conclusions and policy recommendations**

353 The results showed the effectiveness of a systemic approach for detecting hidden interactions
354 among variables. This is particularly true when a complex socio-economic issue like food waste
355 is concerned, and if the data refer to a heterogeneous geographical area like the EU. Rather
356 than adopting arbitrary levels of statistical significance, or imposing an *a priori* model to the
357 data, machine-learned BNs detect the structure of the relationships among variables from the
358 data themselves. This allowed us to uncover new results and to highlight a number of
359 differences compared to Secondi et al. (2015), despite using a similar dataset. While they find

360 the place of residence (urban, semi-urban, rural), the level of education, and the gender of the
361 respondent to be three important determinants of the amount of self-declared food waste, the
362 BN highlighted the role of household size, and of the status of being a student. The age and the
363 country of the respondent were identified as being relevant drivers of food waste by both
364 methodologies. However, while Secondi et al. (2015) argue that richer EU Member States show
365 higher level of waste, the BN suggests that respondents from poorer countries are more likely
366 to waste “50% or more” of their food.

367
368 These findings call for a comprehensive EU strategy, neglected by previous studies on food
369 waste. Due to the country-level heterogeneity identified, such strategy should include both EU-
370 and national-level measures, making an effective use of subsidiarity. Previous studies have
371 grouped the policies addressing food waste into suasive, regulatory, market-based, and public
372 service provision (Aramyan et al. 2016). These policy typologies should be integrated into a
373 mix tailored to individual countries, or groups of countries. Moreover, within these countries,
374 the socio-demographic groups identified by our BN as more incline to waste food should be
375 addressed by means of targeted policy interventions.

376
377 In low-income countries where knowledge of the food waste problem is still limited, formal
378 educational programmes targeting school children and university students, as well as national
379 campaigns targeting middle-aged citizens could be used to raise awareness, while stricter
380 (“command-and-control”; Vittuari et al. 2016) regulations on food safety and management by
381 retail supermarkets could help increase the life of perishable products and discourage
382 overbuying by those wasting “more than 50%” of their food while, at the same time, helping
383 consumers to reify the existence of the food waste problem. At the same time, income support
384 policies could lead the poorest to buy better quality food, less likely to be wasted. These
385 measures should be implemented in synergy with local administrations (i.e. adopting vertical
386 subsidiarity). In higher-income countries, instead, the awareness of environmental problems is
387 more widespread, and local institutions have more resources and a better organisational
388 capability. Here, multi-stakeholder governance of food supply chains (e.g. by involving
389 consumer organizations within the management boards of large-scale retailers, thus
390 implementing horizontal subsidiarity) could be implemented drawing on the experience of the
391 EU Platform on Food Losses and Food Waste (Ibid). Furthermore, market-based instruments
392 could be effectively adopted to reduce household food waste. These include, in particular,

393 negative price-based incentives, like the “pay-as-you-throw” principle applied to organic waste
394 by means of weight and frequency-based schemes (Aramyan et al. 2016).

395

396 BNs allow the identification of dependencies among variables, but not their direction and their
397 mechanisms (i.e. causality). Understanding *why* age and country-level differences occur may
398 be of paramount importance for designing better policy interventions. Nevertheless, the
399 probabilistic understanding of the drivers of food waste we have developed here allows further
400 targeted action and research. Determining the mechanisms behind these drivers could be a key
401 area for this future research. In particular, the reasons why students waste a large amount of
402 food, and especially the complex relationship between food waste and (household or local)
403 income levels may need to be understood. “Mixed-method” approaches might prove useful in
404 combining the strengths of quantitative and qualitative research to better interpret the context
405 of the results (Phyel & Hong 2014).

406

407 Finally, there are some measures that policy-makers can use to assess the quality of evidence
408 presented in scientific papers regardless of the statistical discipline they follow. For example,
409 more reliable evidence might be found in papers that;

- 410 • interpret the results in terms of the size of the effect (with a clear indication of the range
411 of possible outcomes, e.g. confidence limits, standard deviations, probabilities, etc.)
412 rather than in purely statistical terms (e.g. “significantly different”, or “ $p < 0.05$ ”, etc.);
- 413 • use some form of model selection to identify the most suitable structure of a model
414 rather than rely on a single structure alone;
- 415 • carefully select variables with a rationale for inclusion;
- 416 • have a pre-published protocol usable to identify the variables, that will be tested and
417 processed to reduce the biases undertaken by the researcher – this is a popular approach
418 in meta-analysis and systematic review, but can be applied more widely;
- 419 • provide access to data and analysis work flows to allow replication of the study findings
420 (all data and workflows for this analysis are available at
421 https://osf.io/ye9dp/?view_only=4469bc2368a942a59f7ad239427cc8fb).

422

423 Policy-makers may wish to make use of existing, or commission new, systematic reviews or
424 meta-analysis to determine the strength of evidence and direction of effects. Systems models

425 (e.g. BNs) can then be used to place the results from systematic reviews and meta-analysis into
426 a wider policy-relevant context.

427

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436

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- 569

Table 1. Variables included in the dataset used within this paper.

Eurobarometer 388 question	Variable name	States
Q9: Can you estimate what percentage of food you buy goes to waste?	Food waste	More than 50 %
		31 to 50 %
		16 to 30 %
		6 to 15 %
		5 % or less
		None
D3a: What is your nationality? Please tell me the country(ies) that applies(y).	Country	Did not answer
		Austria
		Belgium
		Bulgaria
		Croatia
		Cyprus (Republic)
		Czech Republic
		Denmark
		Estonia
		Finland
		France
		Germany
		Greece
		Hungary
		Ireland
		Italy
		Latvia
		Lithuania
		Luxembourg
		Malta
Poland		
Portugal		
Romania		
Slovakia		
Slovenia		

		Spain
		Sweden
		The Netherlands
		United Kingdom
D2: Gender	Gender	Male
		Female
Q3 Which of the following actions do you think would make the biggest difference in how efficiently we use resources? Reducing waste at home.	Home waste	Yes
		No
Q17: How much litter is there in the area where you live (litter on the street, in natural surroundings, etc.)?	Litter	Quite a lot
		A lot
		None
		Not much
		Don't know
Q6 Do you sort the following types of waste, at least occasionally? Kitchen waste.	Kitchen waste	Yes
		No
D4: How old were you when you stopped full-time education?	Education	Still Studying
		Up to 15
		16-19
		20 years and older
		No full-time education
		Don't know
		Refusal
D5: As far as your current occupation is concerned, would you say you are self-employed, an employee, a	Employ	Employees
		Manual workers
		Not working
		Refusal

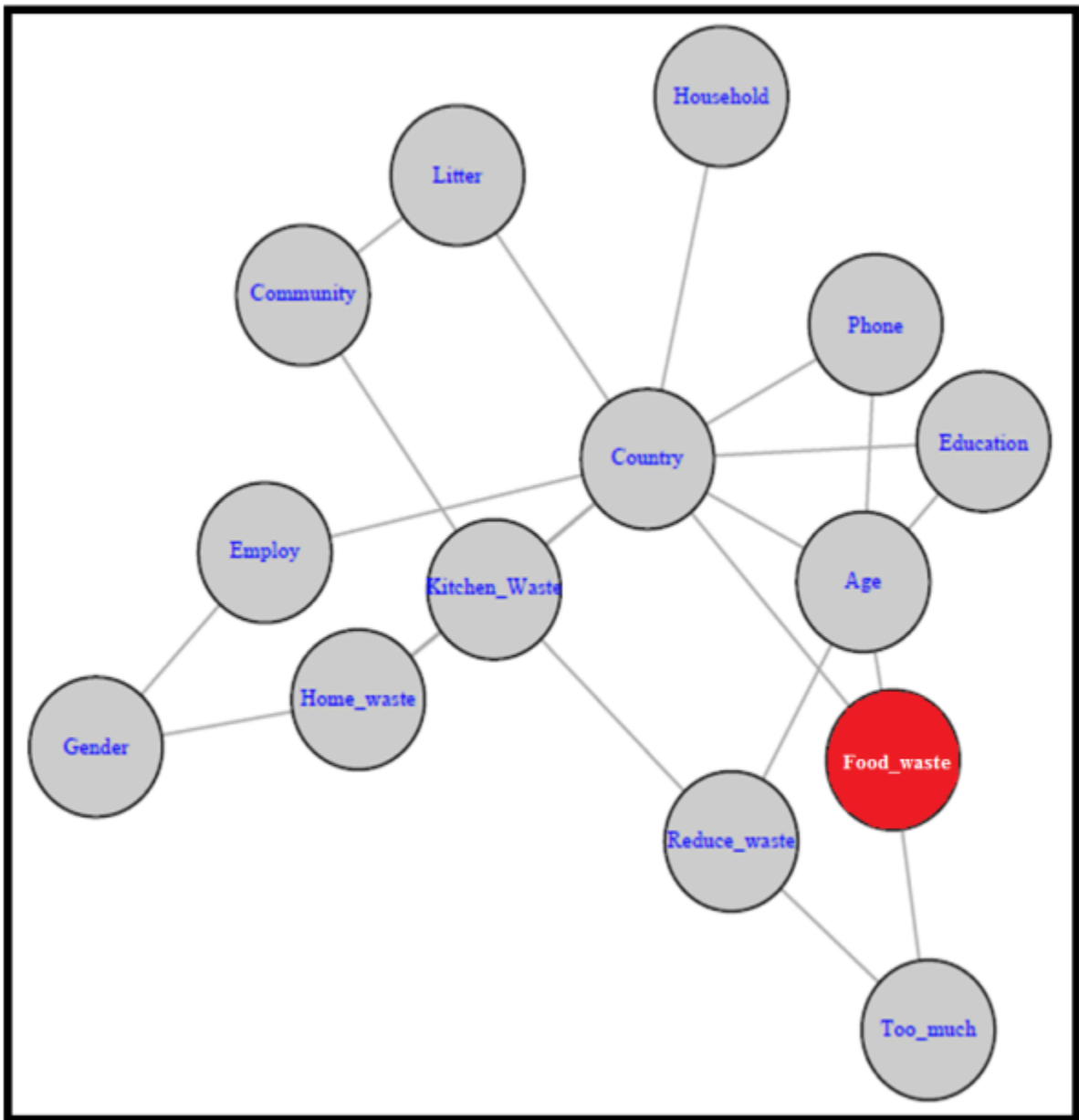
manual worker or would you say that you are without a professional activity?		Self-employed
D1.1 How old are you?	Age	15 - 24 years 25 - 34 years 35 - 44 years 45 - 54 years 55 - 64 years 65 years and older Refused to answer
D18 - Have you got a mobile phone?	Phone	Landline only Mobile and landline
D20 - Have you got a landline phone?		Mobile only
Q4.3 For each of the following statements, please tell me whether you totally agree, tend to agree, tend to disagree or totally disagree. You make efforts to reduce the amount of household waste that you generate.	Reduce waste	Totally agree Tend to agree Tend to disagree Totally disagree
Q4.2: For the following statement, please tell me whether you totally agree, tend to agree, tend to disagree or totally disagree: “Your household is generating too much waste”	Too much	Totally agree Tend to agree Tend to disagree Totally disagree
D22: Could you tell me how many people aged 15 years or more live in your	Household	1 2 3 4+

household, yourself	Don't know
included?	Refused to answer
D13 Would you say you live Community	Large town
in a...?	Rural area or village
	Small or middle-sized town
	Don't know

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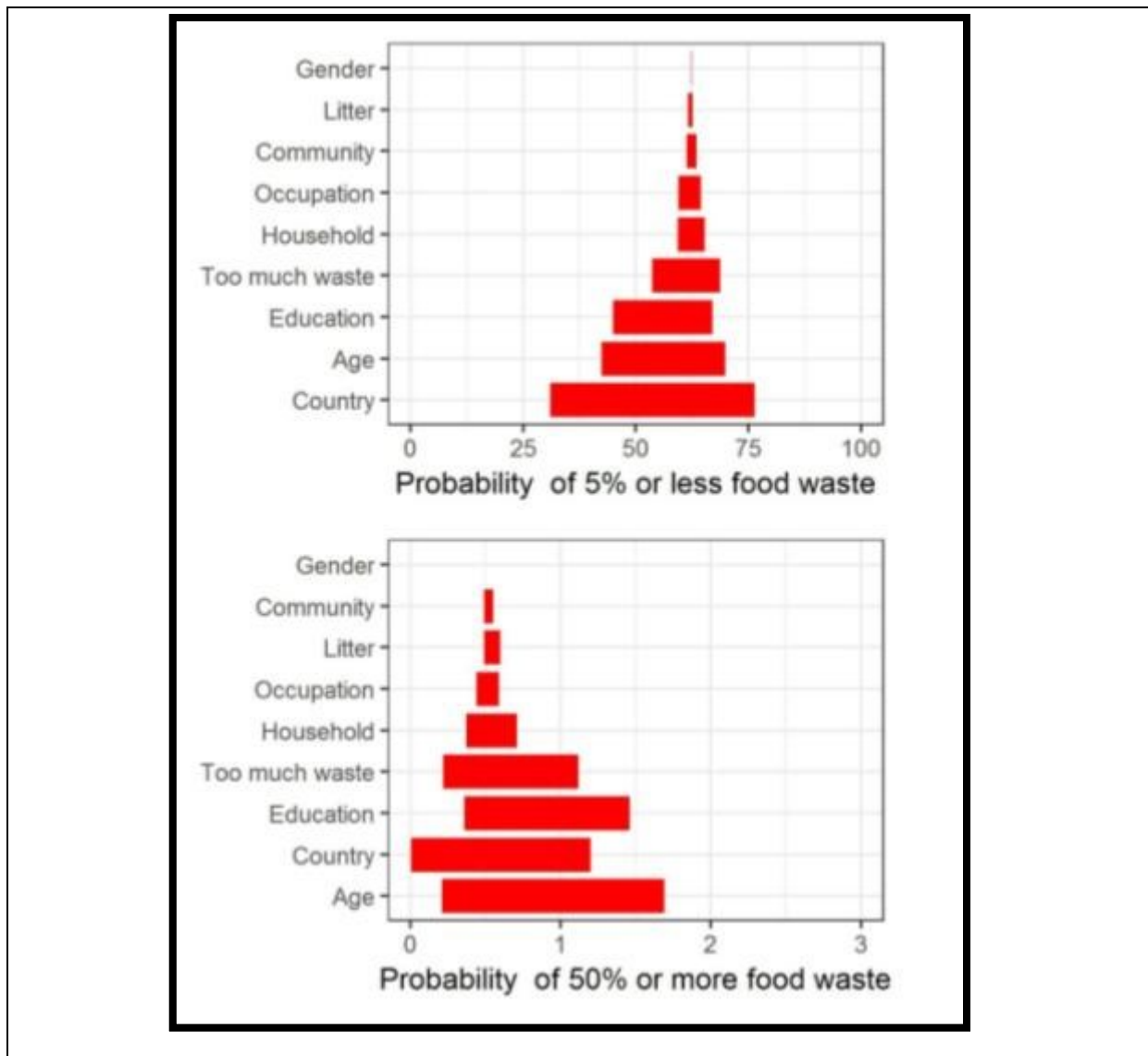
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573

Figure 1. The machine-learnt structure of the Eurobarometer 388 dataset in relation to self-reported food waste (see Table 1 for a description of the variables).

574



575

Figure 2. The sensitivity of the food waste node given the variation of the nine nodes that have the largest effect on it. The largest uncertainty occurs in the state of the “5% or less” (upper graph) when we change the state of the “Country” node (i.e. there is a lot of variation between countries). For the state “50% or more” (lower graph) the largest uncertainty occurs when we vary the “Age” node.

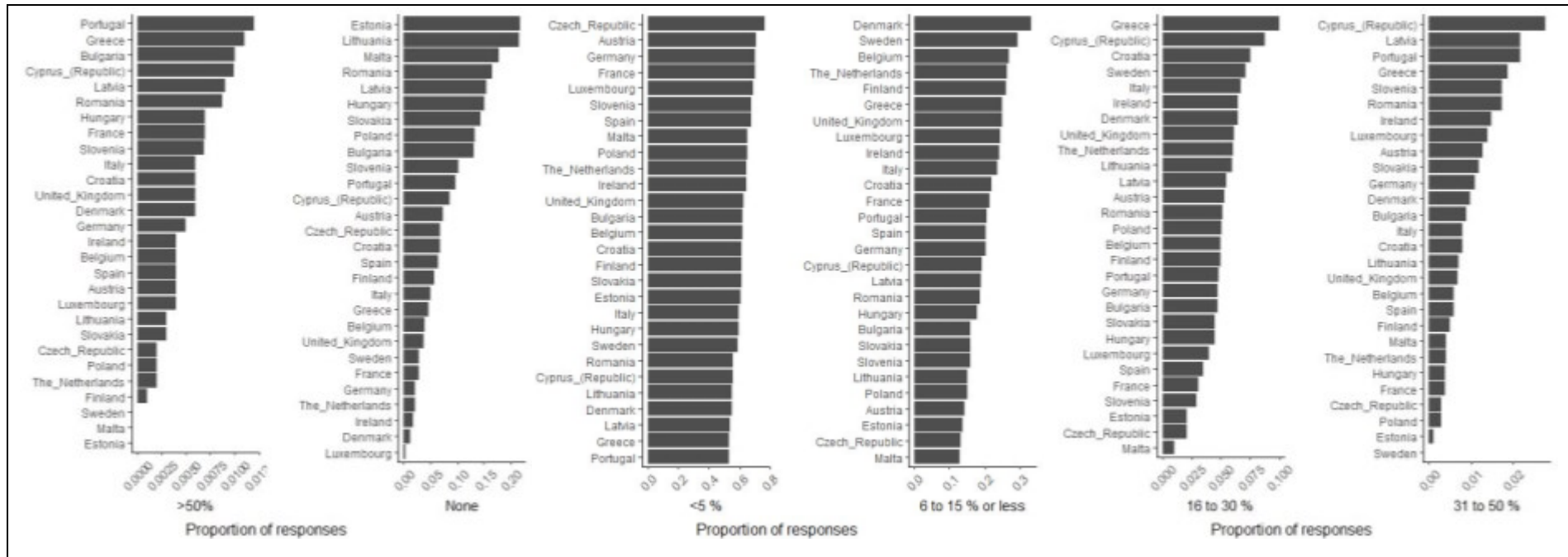
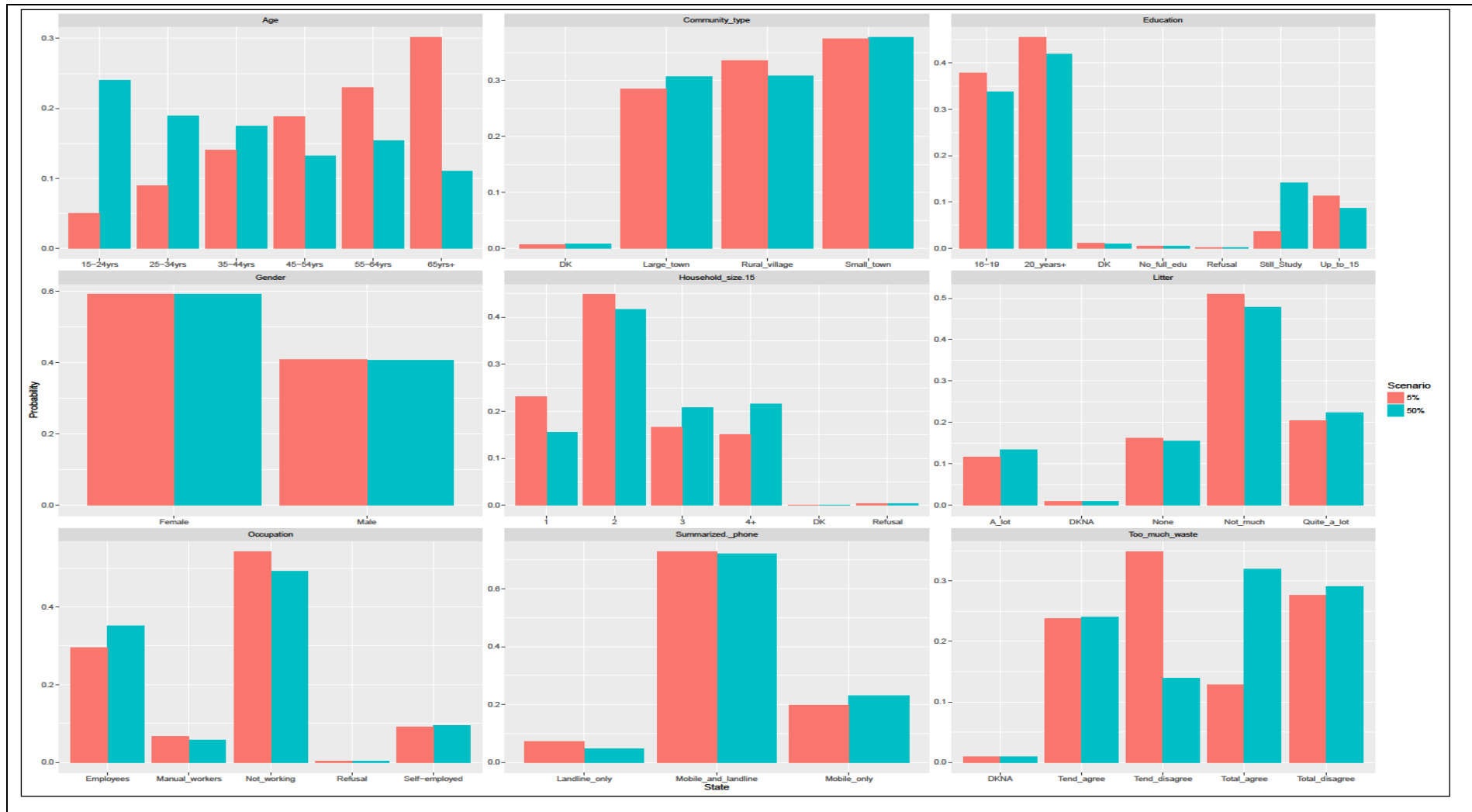


Figure 3. Percentage of respondents who selected each of the six states of the food waste node in each EU Member State.

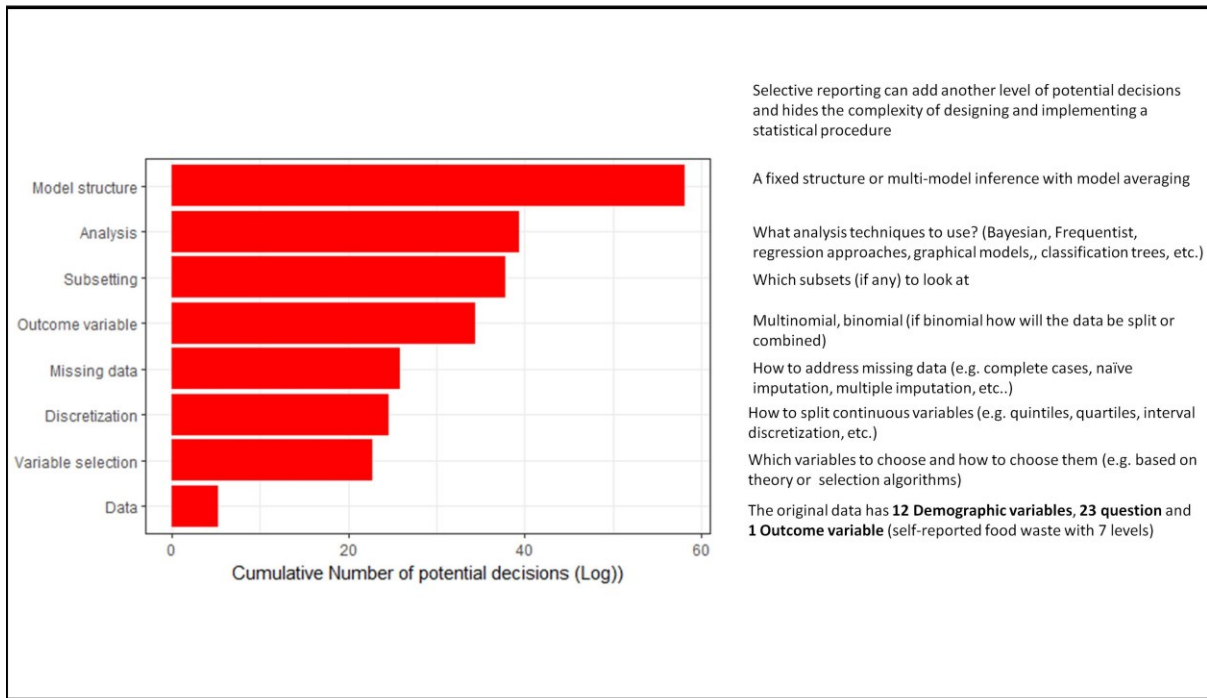


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Figure 4. State of the nodes which show the largest effect on self-reported food waste (apart from country, but including phone ownership) given the states “5% or less” (red bars) and “50% or more” (blue bar) of the food-waste node, respectively



580

581 **Figure 5. An estimation of the cumulative number of potential decisions that a researcher**

582 **needs to take in order to model the Eurobarometer dataset on food waste.**