

1 **Information use and its effects on the valuation of agricultural genetic resources**

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3 Dr Annika Tienhaara<sup>1\*</sup>, Dr Heini Ahtiainen<sup>1</sup>, Prof Eija Pouta<sup>1</sup> & Prof Mikołaj Czajkowski<sup>2</sup>

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5 <sup>1</sup> Natural Resources Institute Finland (Luke), Latokartanonkaari 9, 00790 Helsinki, Finland

6 \*Corresponding author: annika.tienhaara@luke.fi

7 <sup>2</sup> University of Warsaw, Department of Economics and Charles University, Environmental Center;

8 Długa 44/50, 00-241 Warsaw, Poland

## 9 **Abstract**

10 This paper examines the effects of information on stated preferences for an unfamiliar  
11 environmental good: agricultural genetic resources. We define two groups of respondents based on  
12 their use of additional information, and we model information use and its effect on individual  
13 preferences and scale. Our findings indicate that both sociodemographic and attitudinal variables  
14 affect the use of information. We observe individual preference heterogeneity, but no significant  
15 differences in scale between the information groups. The results highlight the importance of genetic  
16 resource conservation and controlling for the effects of information use in choice experiment models  
17 for unfamiliar goods.

18

19 **Keywords:** Agricultural genetic resources; Discrete choice experiments; Environmental valuation;

20 **Information effects**

21 **JEL codes:** Q51, Q57

22

23 **Appendix materials can be accessed online at:**

24 <https://uwpress.wisc.edu/journals/pdfs/LE-98-2-Tienhaara-appA.pdf>

25 <https://uwpress.wisc.edu/journals/pdfs/LE-98-2-Tienhaara-appB.pdf>

26

## 27 1. Introduction

28

29 Stated preference methods, including contingent valuation (CV) and discrete choice  
30 experiments (CE), are often used to examine citizens' willingness to pay (WTP) for environmental  
31 goods, to provide policy-relevant information on environmental values (Hanley and Czajkowski  
32 2019). Nowadays, applications are common for both goods that people are familiar with and have  
33 some experience of, such as water quality (e.g. Hanley et al. 2006; Ahtiainen et al. 2015), and goods  
34 that people may be unfamiliar with or have no practical experience of, such as specific rare species  
35 or biotopes (e.g., Christie and Gibbons 2011; Jobstvogt et al. 2014) or agricultural genetic resources  
36 (AgGR) (Pouta et al. 2014). Regardless of the good, the underlying assumption is that respondents  
37 make informed choices (e.g., Blomquist and Whitehead 1998). This is easier when the good being  
38 valued is familiar to the respondent. However, in the valuation of more unfamiliar goods, the  
39 information provided in the survey plays a more substantial role. This paper focuses on the effects of  
40 information in the valuation of genetic resources: whether respondents use the additional information  
41 provided, what characteristics are related to the use of information, and if and how this information  
42 affects respondents' preferences and WTP.

43 Both the amount and type of information that is presented to respondents require attention in  
44 survey design (Johnston et al. 2017). Including more information about the quality of the  
45 environmental good in a survey can have various effects on WTP: it can increase, have no impact on,  
46 or decrease the WTP (Blomquist and Whitehead 1998). It has been argued that the provision of  
47 relevant information improves respondents' understanding of environmental commodities and  
48 reduces both uncertainty and possible divergence between the true and stated WTP (Hoehn and  
49 Randall 1987). However, increased information in stated preference surveys increases the burden of  
50 information processing and the complexity of the choice process. Increased complexity, in turn,  
51 affects the consistency of respondents' choices and thereby their stated WTP (Berrens et al. 2004).  
52 When faced with difficult choice questions, respondents often tend to use heuristics. Sandorf et al.

53 (2017) suggested that providing information about the environmental good in question before a  
54 valuation task is important, because the more respondents know about the environmental good in  
55 question, the less likely they are to use simplifying strategies, such as attribute non-attendance. As  
56 increasing knowledge helps to avoid, at least to some extent, the use of heuristics, providing  
57 information can be helpful in obtaining more accurate welfare estimates.

58 In addition to the extent of information, the nature of the information also plays a role.  
59 According to Hu et al. (2009), studies assessing the effect of information on consumers' choices have  
60 concluded that positive information tends to reduce adverse reactions, while negative information  
61 tends to reinforce negative responses. Environmental commodities can have beneficial attributes, but  
62 also attributes that can be perceived negatively. Hence, additional information describing these  
63 negative attributes can induce reductions in WTP (Bergstrom et al. 1990).

64 Information provision is important to an individual's decision-making, especially in situations  
65 where considerable uncertainty is involved, for example, in the valuation of unfamiliar goods. It is  
66 often assumed that once information is made available, respondents will access and process it.  
67 However, simply providing information does not imply that all the respondents will read it. The  
68 decision of respondents to access voluntary information is reliant on their previous knowledge of the  
69 topic and personal characteristics (Hu et al. 2009). Furthermore, even if the respondents access the  
70 information provided, it is difficult to assess whether they truly comprehend it. Aanesen et al. (2015)  
71 applied a valuation workshop in order to reduce the problems related to the valuation of an unfamiliar  
72 good (in their case, cold-water coral). The workshop setting allows more extensive provision of  
73 information and also helps researchers to learn how respondents understand the questions and the  
74 information. However, this method is time consuming, especially if the aim is to obtain data that are  
75 representative of the population. In addition, results can be biased by self-selection and the social  
76 desirability effect.

77 The CV literature contains a plethora of studies on information effects and their reasons, as  
78 well as on respondents' cognitive effort (see, e.g., Cameron and Englin 1997; Blomquist and

79 Whitehead 1998; Munro and Hanley 2002; Berrens et al. 2004). Most of these CV studies have found  
80 significant information effects on preferences and values. However, only a few CE studies have  
81 examined the use of information. Hu et al. (2009) and Vista et al. (2009) focused on respondent effort,  
82 indicated by the decision to access optional information made available in the survey and the time  
83 spent on completing the survey. Hu et al. (2009) used data from a CE concerning genetically modified  
84 food to simultaneously model voluntary information access and product choices. They demonstrated  
85 that additional information was accessed rather infrequently, and that those who held critical views  
86 on genetic modification accessed the information more often. There were interlinkages between  
87 information access and choices, but they were complex and varied between individuals. Vista et al.  
88 (2009) examined the effect of time spent on attribute information, choice questions and completing  
89 the survey on preferences, finding no significant effects on parameter estimates. In turn, Curtin and  
90 Papworth (2018) sought to explore whether additional information can shift stated conservation  
91 preferences, concluding that the amount of information provided in the CE affected the conservation  
92 decisions. Emberger-Klein and Menrad (2018) studied how information provision affected  
93 consumers' use of carbon labels. Additional information about the labels encouraged the use of and  
94 preference for carbon labels among consumers and could also affect the purchase decision.

95 Heterogeneity of preferences and heterogeneity in scale across individuals has become an  
96 important consideration in modeling CE responses (Louviere et al. 2002; Louviere 2006; Fiebig et al.  
97 2010; Hensher et al. 2012). Scale represents the variation in the random component of utility relative  
98 to the deterministic component, and scale heterogeneity implies that the scale of the error term varies  
99 across respondents. From the analyst's perspective, a higher mean scale infers that the respondents'  
100 choice behavior appears less random. Regarding unfamiliar goods, it may be especially important to  
101 allow for scale heterogeneity, in addition to individual preference heterogeneity (Christie and  
102 Gibbons 2011). Recent CE studies have investigated information effects and the familiarity of the  
103 environmental good while allowing for scale heterogeneity. Using CE data from a biodiversity  
104 conservation program, Czajkowski et al. (2016) demonstrated that individual-specific preferences

105 and the mean of the scale parameter and its variance in the sample are sensitive to the information  
106 given to the respondents. Christie and Gibbons (2011) interpreted scale heterogeneity as the ability  
107 of respondents to choose, and concluded that accounting for scale heterogeneity can improve the  
108 reliability of the results when valuing unfamiliar or complex goods. Related to AgGR, Pallante et al.  
109 (2016) and Zander et al. (2013), for example, examined both preference and scale heterogeneity.  
110 However, there have been no studies examining the effect of information use in the valuation of  
111 AgGR.

112 Here, we contribute to the stated preference literature on the effect of information use on  
113 respondents' choices and WTP for an unfamiliar good, i.e., AgGR. Our CE survey offered the  
114 respondents an opportunity to access additional information on the environmental good being valued,  
115 similarly to Hu et al. (2009). We examine the determinants of voluntary information acquisition and  
116 the effect of accessing the information on respondents' preferences and scale, allowing for individual  
117 preference and scale heterogeneity. The data come from a CE survey on AgGR, which include all  
118 animal and plant species and varieties of interest in agriculture. Although the public is likely to be  
119 aware of agricultural production and its impacts on the environment, specific aspects, such as the  
120 conservation of genetic resources, are likely to be unfamiliar to at least some of the respondents. This  
121 setting provides an excellent prospect for examining the influence of information on preferences for  
122 unfamiliar environmental goods in a CE (Pouta et al. 2014).

123 The paper is organized as follows: Section 2 discusses genetic resource conservation in  
124 Finland and introduces the survey and data, section 3 describes the statistical approach, section 4  
125 presents the results, and section 5 discusses and concludes the analysis.

126

127 2. Survey and data

128

129 **Conservation of agricultural genetic resources in Finland**

130

131 Agricultural intensification has caused significant changes in the utilization of AgGR in recent  
132 decades. Consequently, many previously common animal breeds and crop varieties are currently on  
133 the verge of extinction worldwide. In Finland, the majority of old, indigenous crop varieties and the  
134 Finnish landrace pig are already extinct. Furthermore, Northern Finncattle and Kainuu Grey sheep  
135 are endangered, and the populations of Finnhorse, native chicken, Åland sheep, native goat and  
136 Western and Eastern Finncattle are described as vulnerable according to the FAO classification  
137 (MMM 2018).

138

139 International agreements, such as the Convention on Biological Diversity (1992), the Global  
140 Plan of Action for Animal Genetic Resources (FAO 2007), and the United Nations strategic plan for  
141 biodiversity (CDB 2011), guide the conservation policies for AgGR. National programs to support  
142 the conservation of genetic resources in Finland were initiated in 2003 for plants and in 2005 for farm  
143 animals. There has been some progress in actioning the conservation programs, but they have not  
144 been fully implemented due to a lack of resources and political interest in conservation. In addition,  
145 the economic benefits of such programs are poorly known. Thus, the present study aims to estimate  
146 citizen's use and non-use benefits from the conservation of AgGR, for policy-making support,  
147 especially focusing on the effects of information in the context of valuing unfamiliar goods.

148

## 149 **Data collection**

150

151 The CE survey was carried out during the summer of 2011 using a probability-based Internet  
152 panel of a private survey company, Taloustutkimus. The survey questions, and especially the choice  
153 experiment, were tested with a pilot study ( $n = 138$ ). For the final survey, a random sample of 6200  
154 respondents was selected and 2426 responses were obtained. Out of these, 1495 completed the whole  
155 survey. The response rate for the final survey was therefore 39% and 24%, respectively. Based on the  
156 sociodemographic information, in comparison with the statistics for the general Finnish population

157 (Table 1), the data were an adequate representation of the population. The proportions of females,  
158 people with a higher educational level, and people living in Southern Finland were similar in the data  
159 and population. However, the respondents were somewhat older, had a higher income, and were less  
160 likely to have children compared with the population.

161

## 162 **Survey design**

163

164 The survey had five sections, with questions on environmental issues in agriculture,  
165 familiarity with and attitudes toward AgGR, environmental values (the CE), willingness to purchase  
166 products made from traditional varieties and breeds and, finally, the respondent's background. The  
167 survey began with a question on the respondents' perceived importance of different agri-  
168 environmental measures. This was followed by a short description of the most common Finnish  
169 AgGR (native animal breeds and plant varieties), for which the respondents evaluated their  
170 familiarity. Next, the conservation of AgGR in Finland was briefly highlighted, and the respondents  
171 were then presented with two Internet links that allowed access to additional information on animal  
172 and plant genetic resources, respectively (see Appendix A). This voluntary additional information  
173 package included the motivation for conservation, descriptions of different conservation methods,  
174 and information on the sustainable use of genetic resources. We recorded the time respondents used  
175 to read this additional information. The provision of voluntary information enabled the identification  
176 of respondents who accessed the links, as well as documenting how much time they spent on these  
177 information pages. This approach was similar to Hu et al. (2009), who provided voluntary access to  
178 additional information. In our case, however, the choice tasks and information acquisition were not  
179 simultaneous, but instead, the information was provided before the CE. The information page with  
180 the links was followed by questions about the perceived importance of animal and plant genetic  
181 resources. The survey then presented the current state of conservation (the status quo) and proceeded  
182 to the CE.

183 The CE was framed by explaining that many of the Finnish native animal breeds and plant  
184 varieties are endangered and their preservation requires special measures. After familiarizing the  
185 respondents with the current level of preservation, they were presented with a program that would  
186 increase the conservation of breeds and varieties on farms (*in situ*) and in gene banks (*ex situ*). The  
187 conservation program included five attributes, each containing three levels, with first level always  
188 presenting the status quo level (Table 2). Native animal breeds in gene banks and on farms were  
189 presented to the respondent as single attributes, instead of having separate attributes for each animal  
190 breed, in order to avoid choice tasks that were too taxing. However, in the analyses, individual animal  
191 breeds were treated as separate attributes. The number of traditional ornamental plant varieties was  
192 given as verbal expressions, as the total number of varieties was unknown and mapping of the  
193 varieties is still ongoing. The cost attribute was specified as an increase in income tax over a 10-year  
194 period (2012–2021).

195 In the CE, the respondents faced six choice tasks (see Table 3 for an example), each containing  
196 two policy alternatives and the status quo option. After each choice task, the respondents evaluated  
197 the certainty of their choice on a scale from 1 to 10 (1 = completely uncertain; 10 = completely  
198 certain).

199 The experimental design was created with Ngene software (v. 1.0.2), employing a Bayesian  
200 D-efficient design (ChoiceMetrics 2010). Efficient designs aim to capture the maximum amount of  
201 information from each choice situation. This is done by finding the design with minimal standard  
202 error values, thereby producing more reliable parameter estimates (see, e.g., Rose and Bliemer 2009).  
203 To generate efficient designs, it is necessary to specify priors for the parameter estimates. Zero priors  
204 were used in the pilot design, but the final design utilized the parameter estimates obtained from the  
205 pilot study. The final design consisted of 180 choice tasks blocked into 30 subsets, which resulted in  
206 six choice situations for each respondent. A more detailed description of the experimental design is  
207 presented in Pouta et al. (2014).

208

## 209 3. Statistical models

210

211 In the statistical modeling, we examined the use of information and its effects on scale,  
212 preferences, and WTP. First, a logistic regression model (e.g., Greene 2007) was estimated to  
213 examine the use of information. The dependent variable in the logit model was a binary variable  
214 describing information use, defined according to the time the respondent spent on the additional  
215 information pages for the native animal breeds and plant varieties. Since only a small proportion of  
216 respondents read only one of the two information pages and the effects of accessing information about  
217 animals and plants had very similar effects on preferences in preliminary tests, we combined animal  
218 and plant information into one variable<sup>1</sup>. The respondents were considered to have perused the  
219 information if they had spent 30 s (close to the median time) or more on either of the information  
220 pages. A robustness check was conducted for the choice of cut-off time using (1) a linear function,  
221 (2) a logarithmic function, and (3) by defining alternative discrete thresholds, based on other quartiles  
222 of time distribution. The results of the sensitivity analysis were consistent and robustness was  
223 confirmed. In addition to socio-demographic variables, independent variables included the perceived  
224 responsibilities for the conservation of AgGR, the respondent's familiarity with native breeds and  
225 varieties, and the perceived importance of preserving AgGR relative to other environmental  
226 protection measures. The descriptive statistics for the variables included in the logit model are  
227 presented in Table 4.

228 Second, respondents' utility function parameters were modeled using the stated choices they  
229 made in the CE component of the survey. We utilized the random parameters mixed logit (RP-MXL)  
230 model (McFadden and Train 2000; Hensher and Greene 2003), which allows for incorporation of  
231 unobserved preference and scale heterogeneity (Hess and Train 2017). Following Czajkowski et al.  
232 (2014), we controlled for scale or preference differences between respondents who did/did not access  
233 additional information while modeling their choices jointly.

234 Modelling discrete choice data follows the random utility theory (McFadden 1974). In the  
 235 random utility framework, an individual is assumed to maximize the utility by choosing the  
 236 alternative with the highest utility from a given choice set. An individual  $i$ 's utility from selecting  
 237 alternative  $j$  in situation  $t$  can be expressed as:

$$238 \quad U_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt}. \quad [1]$$

240  
 241 The utility can be divided into two parts: the observed characteristics (i.e., choice attributes),  
 242  $\mathbf{x}_{ijt}$ , and the random component,  $\varepsilon_{ijt}$ , which includes unobservable factors that affect individuals'  
 243 choices. Individual-specific taste parameters ( $\boldsymbol{\beta}_i$ ) allow differences in preferences among the  
 244 respondents. To account for preference differences associated with accessing the voluntary  
 245 information, a binary indicator  $z$  for accessing information and a vector  $\boldsymbol{\delta}$  of its estimated attribute-  
 246 specific effects can be added to the multivariate distribution of these parameters  $\boldsymbol{\beta}_i = f(\mathbf{b} + z_i\boldsymbol{\delta}, \boldsymbol{\Sigma})$ ,  
 247 where  $\mathbf{b}$  is a vector of sample means and  $\boldsymbol{\Sigma}$  is a variance-covariance matrix.<sup>2</sup>

248 The random component of the utility function ( $\varepsilon_{ijt}$ ) is usually assumed to identically and  
 249 independently have an extreme value type-1 distribution with a constant variance  $var(\varepsilon_{ijt}) = \pi^2/6$ ,  
 250 leading to the following specification:

$$251 \quad U_{ijt} = \sigma_i \mathbf{x}_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt}, \quad [2]$$

252  
 253 where  $\sigma_i$  is the 'scale' parameter. As the utilities are ordinal, the absolute value of utility has no  
 254 meaning and only differences in utilities matter (Hensher, Rose & Greene 2015). Hence, this  
 255 specification still represents the same preferences for individual  $i$ . Note that since the scale and  
 256 preference parameters enter the model as a multiplication, they are not separately identifiable.  
 257 However, this does not restrict model applicability, because utility function parameters do not have  
 258 an absolute scale and can only be interpreted in relation to zero and each other.  
 259

260 Accessing information is likely to influence the variance of the random component of the  
 261 utility function (scale), that is, the level of randomness of choices from the modeler's perspective. As  
 262 a result, since the variance of the error term is normalized in the model, parameter estimates of all the  
 263 utility function parameters would increase or decrease relative to those who have not accessed  
 264 information and whose scale is used as a baseline. Scale differences associated with accessing  
 265 information can be controlled by defining  $\sigma_i = \sigma(\exp(\lambda z_i))$ , where  $z$  is a binary indicator for  
 266 accessing information and  $\lambda$  is a parameter capturing its effect for scale, relative to the baseline  
 267 group of individuals (e.g., Czajkowski et al. 2015; Ruokamo et al. 2016).

268 As we were interested in the marginal rates of substitution with respect to the monetary  
 269 attribute  $p$ , we estimated the models in WTP space (Train and Weeks 2005), in addition to preference  
 270 space. The money-metric utility function can be obtained as follows:

$$271 \quad U_{ijt} = (\alpha p_{ijt} + \mathbf{Y}_{ijt} \mathbf{b}) + \varepsilon_{ijt} = \alpha(p_{ijt} + \mathbf{Y}_{ijt} \boldsymbol{\beta}) + \varepsilon_{ijt}. \quad [3]$$

272  
 273 In this specification, the vector of parameters  $\boldsymbol{\beta} = \mathbf{b}/\alpha$  can be directly interpreted as a vector of  
 274 marginal WTPs for the non-monetary attributes  $\mathbf{Y}_{ijt}$ , making the interpretation of the results easier.  
 275 Here, we can also define  $\boldsymbol{\beta}_i = f(\mathbf{b} + z_i \boldsymbol{\delta}, \Sigma)$ , which conveniently allows us to interpret  $\mathbf{b}$  as the  
 276 mean WTP for a base treatment and  $\mathbf{b} + z_i \boldsymbol{\delta}$  as the mean WTP for other treatments (accessing  
 277 information).  
 278 information).

279 The model is estimated using maximum likelihood techniques. An individual will choose  
 280 alternative  $j$  if  $U_{ijt} > U_{ikt}$ , for all  $k \neq j$ , and the probability ( $P$ ) that alternative  $j$  is chosen from a  
 281 set of  $J$  alternatives is given by:

$$282 \quad P(j|J) = \frac{\exp(\sigma_i \mathbf{x}_{ijt} \boldsymbol{\beta}_i)}{\sum_{k=1}^J \exp(\sigma_i \mathbf{x}_{ikt} \boldsymbol{\beta}_i)}. \quad [4]$$

283

284 There exists no closed form expression of Eq. (4), but it can be simulated by averaging over  
285  $D$  draws from the assumed distributions (Revelt and Train 1998). Maximizing the log-likelihood  
286 function gives estimates for the parameters.<sup>3</sup>

287 In the modeling, attributes were dummy-coded, except for the cost attribute, which was  
288 specified as continuous. All parameters were modeled as random and they were assumed to follow  
289 normal distributions, except cost, which was assumed to be negative log-normally distributed.  
290 Sensitivity analysis using different specifications for the time used to access information confirmed  
291 the robustness regarding the effect on preferences.<sup>4</sup>

292

## 293 4. Results

294

### 295 **Familiarity and use of information**

296

297 As hypothesized, the responses demonstrated that many respondents were unfamiliar with  
298 several native animal breeds and plant varieties. In general, people had heard about or had experience  
299 of native animal breeds more often than plant varieties. Over 30% of respondents had never heard of  
300 about 5 of the 10 animal breeds and plant varieties presented in the survey. Between 5 and 47% of  
301 respondents had no prior knowledge, depending on the breed or variety.

302 Out of the 1,495 respondents, 64% spent over 30 s reading at least one of the two additional  
303 information pages. The median response time for completing the whole survey was approximately  
304 15 minutes. The results of the logit model that explained the use of information are presented in Table  
305 5. According to these results, female and older respondents preferentially read additional information.  
306 The likelihood of reading the information also increased if the respondent considered the conservation  
307 of genetic resources to be the responsibility of taxpayers, but decreased if s/he considered the  
308 conservation as the responsibility of farmers. In our case, the importance of preserving native breeds  
309 and varieties did not play a role in information acquisition. Instead, the respondent's familiarity with

310 the native breeds and varieties negatively impacted on the use of the information. This behavior could  
311 suggest that those who had the least knowledge and experience at the outset were more likely to  
312 obtain additional information in the course of the survey. The educational and income level of the  
313 respondents did not affect their use of information.

314

### 315 **Effects of information on respondents' preferences, scale, and willingness to pay (WTP)**

316

317 We first examined whether the use of information affected the frequency of choosing the  
318 status quo alternative or bid acceptance. There was a noticeable difference ( $p = 0.000$ ) in choosing  
319 the status quo alternative between the information groups. Respondents who read/did not read the  
320 additional information chose the status quo in 19% and 33% of the choice sets, respectively. The  
321 group that read the information had a larger share of respondents accepting the smaller bids, but there  
322 appeared to be no difference between the groups for higher bids (Appendix B).

323 Next, we examined the effects of accessing additional information on the respondents'  
324 preferences and scale. Table 6 presents the results of the RP-MXL models in the preference space,  
325 with correlated parameters<sup>5</sup> in three specifications: assuming that accessing information only causes  
326 differences in scale (Model 1), assuming that accessing information can influence the means of the  
327 preference parameters and scale (Model 2), and allowing for the independent effect for means and  
328 standard deviations of preference parameters (Model 3). The models included 9484 observations from  
329 1608 respondents.

330 The RP-MXL Model 1 (Table 6) included all respondents (both those who read the additional  
331 information and those who did not), and there were no assumed differences in preferences between  
332 the information groups. However, the mean of the scale parameter was allowed to differ between  
333 groups. Most of the conservation parameters in Model 1 were significant and of the expected sign,  
334 with increases in the protection of native breeds and varieties increasing utility. The respondents  
335 tended to choose policy alternatives instead of the status quo. An increase in the program cost was

336 associated with negative utility, as expected. The highest utility changes resulted from the  
337 conservation of plants in gene banks and on farms, as well as cattle breeds on farms. Only the  
338 attributes for preserving food plant varieties, native chickens in gene banks, and the lower level of  
339 change for increasing the number of sheep breeds on farms were nonsignificant.

340 Model 1 indicates that accessing information increases scale, namely it reduces the error term  
341 variance. In other words, respondents' choices appear less random from the modeler's perspective.  
342 However, the comparison with Model 2, in which parameters of the means of each attribute can  
343 depend on whether the information was accessed or not, indicates that Model 1 is overly restrictive.  
344 Since the models are nested, one can use the likelihood ratio test to confirm this (see Table 6 for  
345 details). As a result, we concluded that the scale results observed in Model 1 are driven by the effect  
346 of accessing information on selected mean parameters, as indicated by significant interactions with  
347 'information accessed' in Model 2 (Table 6). In particular, respondents who accessed information  
348 were, on average, less likely to choose the status quo, had stronger preferences for increasing the  
349 number of food plants and native cattle breeds on farms, as well as goats in gene banks, and had a  
350 significantly lower marginal utility of money (and, hence, an expected higher WTP). Accessing  
351 information did not appear to affect the mean preference parameters for other attributes. In addition,  
352 once differences in means were controlled, the interaction of scale with a dummy variable for  
353 accessing information was no longer significant. Namely, there was no consistent statistical  
354 difference in the variances of preference parameters between those who did/did not access the  
355 additional information.

356 Model 3, with two information groups, allows for the independent effect of accessing  
357 information on the means and standard deviations. A comparison of the parameter estimates between  
358 the information groups revealed that not only were many of the attribute coefficients higher, but there  
359 were also more significant variables for the group that had accessed the additional information  
360 relative to those who did not. Moreover, these respondents were less willing to choose the status quo  
361 alternative and derived higher utility from improvements related to preserving native food varieties

362 on farms, ornamental varieties in gene banks, and native horse and sheep breeds. The results indicate  
363 that those who had familiarized themselves with the information obtained more utility from the  
364 improvements compared with those who had not accessed the information<sup>6</sup>. However, based on the  
365 likelihood ratio test, there was no significant difference in the model fit between Model 3 and Model  
366 2 ( $p = 0.999$ ).

367 Next, we compared the differences in the respondents' WTP resulting from accessing  
368 additional information. Even though we have established that additional information can influence  
369 respondents' preference parameters, this is not necessarily equivalent to causing significant  
370 differences in their mean WTP, especially if the effects of preferences for attributes and cost are not  
371 proportional. Therefore, we estimated the same three specifications of the RP-MXL model with  
372 correlations in the WTP space. The results, presented in Table 7, can readily be interpreted as  
373 marginal WTP (€/year), and show that differences in WTP were fairly consistent with the differences  
374 in respondents' preferences. Table 7 summarizes the WTP measures for Model 2 and Model 3. Model  
375 2 shows that in this study, accessing information could be associated with significant differences in  
376 the mean WTP for selected attributes, but not necessarily with significant differences in the scale or  
377 standard deviations of the WTP.

378 Based on Model 3, we can see that compared to the respondents who did not access the  
379 information, those who accessed the information were, on average, willing to pay €6 more for  
380 increasing the number of food plants on farms (from 7 to 2000), approximately €9 more for banking  
381 ornamental plants, and €20 and €5 more for banking native goats and horses, respectively.  
382 Furthermore, they were willing to pay about €25 more for increasing the number of native cattle  
383 breeds on farms, as well as €12–24 more for increasing the number of native sheep breeds on farms.  
384 At the same time, their implied WTP for the status quo policy was about €44 lower, indicating that  
385 they were generally willing to pay more for implementing the new policy than respondents who did  
386 not access the additional information.

387 The WTP for the conservation program with a low level of improvements was €63.38 for  
388 those respondents who did not access the information, whereas the corresponding value for the  
389 respondents who used the information was nearly twice as much (€120.26). When a conservation  
390 program with high levels of improvement was considered, the WTP for the group not accessing the  
391 additional information barely changed (€67.17), while for those who accessed the information, the  
392 WTP further increased to €169.97.

393 Overall, the group that accessed the information had a higher WTP for all attributes when  
394 compared with the group that did not access the information, except for the lower improvement of  
395 food plants on farms. All other WTP measures were of the expected sign, but the group that did not  
396 access the information had a significant and negative WTP for the high improvement level of food  
397 plants banked and the low improvement level of native sheep breeds on farms.

## 398 399 5. Discussion and conclusions

400  
401 This study investigated the voluntary use of additional information and information effects in  
402 a CE setting. The empirical application concerned the conservation of AgGR (native breeds and  
403 varieties) in Finland, an environmental good that is unfamiliar to many people. Respondents were  
404 divided into two groups based on the time they spent reading the additional information in the Internet  
405 survey. We examined the determinants explaining the use of information with the logit model and the  
406 effect of information use on respondents' preferences and scale with the RP-MXL models.

407 The logit model results suggested that respondents who had read the additional information  
408 were more likely to be female, older, and perceived the conservation of genetic resources to be the  
409 responsibility of taxpayers. The respondents who were more familiar with native animal breeds and  
410 plant varieties, and those who felt that conservation was the responsibility of farmers, were less likely  
411 to read the additional information. These results are, in part, similar to those of Hu et al. (2009), who  
412 modeled information access in a CE concerning genetically modified food. In that study, male

413 respondents and those who were employed or had a higher income were less likely to access the  
414 information, and the more children the household had, the lower was the likelihood of information  
415 access. Conversely, being a member of a consumer group or a rural resident increased the likelihood  
416 of accessing the information.

417 Altogether, in our study, the respondents showed support for the conservation of native breeds  
418 and varieties. However, the results of the RP-MXL models indicate that there was heterogeneity in  
419 preferences and WTP between those who accessed/did not access the additional information, with  
420 voluntary information access being associated with higher welfare estimates. The respondents who  
421 had read the additional information chose the status quo alternative less frequently, and their choices  
422 could be explained by several environmental attributes characterizing the conservation program of  
423 AgGR. The choices of the respondents who did not read the information were associated with fewer  
424 significant conservation attributes, and the attribute coefficients were lower than for those having  
425 read the information.

426 This finding could indicate that those who have more information on AgGR obtain greater  
427 benefits from their conservation, and that providing the public with additional information on policies  
428 to conserve AgGR may increase the support for such policies. As our findings pertain to this specific  
429 case, their wider applicability to other unfamiliar goods should be investigated. Another possible  
430 explanation could be that those respondents who had read the additional information were already  
431 more interested in the environmental good and so would be more likely to support the conservation  
432 programs, regardless of the information. However, our results do not corroborate this alternative  
433 explanation, as information acquisition was not significantly explained by the attitudes toward the  
434 importance of conserving AgGR.

435 The findings concerning significant information effects are consistent with several previous  
436 studies (e.g., Tisdell and Wilson 2006; van Til et al. 2009; Chalak and Abiad 2012; Bieberstein et al.  
437 2013). Although Hu et al. (2009) found an interdependence between information access and product  
438 choices, there was a significant variation across individuals.

439 Our findings indicated that there was no significant difference in the mean scale between the  
440 information groups after allowing the mean parameters for the attributes to differ. Even though the  
441 covariate of scale was significant in Model 1, it was driven by the effect of accessing information on  
442 selected mean parameters, as shown by the comparison with Model 2. These results differ from those  
443 obtained by Czajkowski et al. (2016), who found that respondents who were given more information  
444 in the CE made less random choices. Also, in contrast to Christie and Gibbons (2011), who stated  
445 that it is important to control the scale heterogeneity when the good in question is unfamiliar to the  
446 respondents, we did not find significant scale heterogeneity after the mean parameters for the  
447 attributes were allowed to differ.

448 Even though the information affected respondents' choices, some attribute coefficients for the  
449 conservation program were similar across models and information groups. These attributes included  
450 the conservation of plants on farms, horses in gene banks, and cattle breeds on farms. Willingness to  
451 support the conservation programs was lower for the group that did not read the information compared  
452 with those who read the information, especially at low-cost levels.

453 Although we found significant differences between the information groups, defined based on  
454 the time spent reading the additional material, setting the cut-off time to 30 s was arguably arbitrary.  
455 Although the sensitivity analysis regarding the cut-off time demonstrated that the results were  
456 consistent and that, in general, the more time was used to access information, the lower the  
457 preferences for the status quo and the more preferred selected attributes were, we cannot be sure that  
458 information access was associated with an increase in a respondents' knowledge level. Testing the  
459 knowledge level of respondents before and after the possible information access may have provided  
460 certainty on the effect of information. However, it is more difficult to find non-irritating approaches  
461 for testing the ability of respondents to assimilate new information in online surveys than in valuation  
462 workshops (e.g., Aanesen et al. 2015). Our results demonstrated that information access was not  
463 significantly correlated with the educational level. Based on the high reading skills of Finns (PIRLS  
464 <https://timssandpirls.bc.edu/pirls2016/index.html>), we can also assume that reading comprehension

465 is not a problem in information provisioning. Still, we recommend that future research should  
466 investigate ways of properly identifying how much effort respondents actually put into reading the  
467 provided material in stated preference surveys. More information is required on information effects  
468 in CE, for example, examining the relationship between uncertainty and information access, and  
469 whether information use affects respondent uncertainty.

470 As the data for this study were collected in 2011, the time gap poses a potential problem.  
471 However, studying the link between information and preferences is still important. In addition, the  
472 number of studies (especially valuation studies) related to native animal breeds and plant varieties is  
473 still very limited. As there have been no events that could be expected to cause a major change in  
474 peoples' knowledge concerning traditional breeds and varieties or their preferences, our results can  
475 still be used for predicting the current preferences of the Finnish population.

476 Czajkowski et al. (2016) raised the issue of how well-informed preferences should be before  
477 they are used for cost–benefit analysis or policy-making, and how much information should be  
478 provided to the survey respondents. Our results demonstrated that even though neutral information  
479 was available, only about 60% of respondents studied the information and used the opportunity to  
480 familiarize themselves more with the environmental good. Promisingly, the respondents who were  
481 not familiar with the good at the outset were more interested in reading the information. This outcome  
482 is encouraging from a policy standpoint, as it suggests that the share of well-informed respondents  
483 can be increased by providing access to additional voluntary information.

484 In the conservation of AgGR, there are no strong disagreements between stakeholder groups.  
485 An interesting future topic would be to examine how respondents use information from different  
486 standpoints, and whether they tend to select the information that is congruent with their existing  
487 perceptions or extend their understanding with a new type of information that could, however, make  
488 the choice process more demanding.

489

490

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Table 1. Sociodemographic profile of the respondents and the population

Sociodemographic characteristic	In the data	In the population <sup>a</sup>
Proportion of females, %	48	51
Mean age, years	52	47
Proportion of people with a higher educational level, %	24	23
Proportion of people living in households with a gross income under €40,000, %	43	53
Proportion of people with children (<18 years) in the family, %	35	40
Proportion of people living in Southern Finland, %	40	41

<sup>a</sup> Source: Statistics Finland (2010; www.stat.fi)

Table 2. Attributes of conservation programs and their levels

Attribute	Description	Current state/status quo	Level (unit)
Native food plant varieties in gene banks	Native food plants are stored in a gene bank, either as seeds or plant parts.	The gene bank contains seeds from about 300 landrace varieties. Plants that are added vegetatively (e.g., berry and apple varieties) are missing.	300, 400, 500 (number of plants)
Farms growing native food plants	Farmers and hobby gardeners cultivate native food plants on farms or in gardens.	Seven farms grow seeds of native food plants with agri-environmental support. Other activities than growing seeds are not supported.	7, 500, 1000 (number of farms)
Native ornamental plant varieties mapped and in gene banks	Scientists identify and register native ornamental plants. Varieties are preserved in a gene bank, either as seeds or plant parts.	Only a small proportion of the native ornamental plants are known. Storage in the official gene bank is not provided.	A small proportion, about half, the majority (proportion of plants)
Native breeds in gene banks	Landrace breeds are kept in a gene bank as gametes and embryos.	The gene bank contains Western, Eastern and Northern Finncattle, as well as Finnsheep, and Åland and Kainuu sheep. Native chicken, goat and horse breeds are missing from the gene bank.	3 cattle breeds and 3 sheep breeds (status quo level), + all combinations of goat, horse and chicken breeds (breeds)
Native breeds on farms	Native breeds are kept on farms in their natural environment. A breed is considered to be endangered if the number of females is less than 1000.	Farms secure goat, horse and chicken breeds, Finnish sheep and Western Finncattle. Eastern and Northern Finncattle, as well as Åland and Kainuu sheep, are endangered.	1 cattle breed, 1 sheep breed, goat, horse and chicken (status quo level), + all combinations of additional 1–2 cattle and sheep breeds (breeds)
Cost	Cost for taxpayers, €/year during 2012–2021.	No additional costs.	0, 5, 20, 40, 80, 100, 150, 300 (€)

Table 3. Example of a choice task

Attribute	Current state	Conservation program A	Conservation program B
Native food plant varieties in gene banks	Approximately 300	400	400
Farms growing native food plants	7 farms	2000 farms	1000 farms
Native ornamental plant varieties mapped and in gene banks	Some	The majority	About half
Native breeds in gene banks	3 cattle breeds 3 sheep breeds	<b>Current +</b> Chicken Goat Horse	<b>Current +</b> Goat
Native breeds on farms	Goat Horse Chicken Finnsheep Western Finncattle	<b>Current +</b> Northern Finncattle	<b>Current +</b> Western Finncattle Åland sheep
Cost for taxpayer €/year during 2012–2021	€0/year	€80/year	€200/year
I support the alternative	( )	( )	( )

Table 4. Variables used in the logit model

Variable	Description	Mean	Standard deviation	Min	Max
Information	Time spent on at least one of the additional information pages is more than 30 seconds	0.64	0.48	0	1
Gender	1 if female, 0 if male	0.48	0.50	0	1
Age	Respondent's age, continuous	52.31	14.28	19	80
Income	Household gross income (thousands €/year), continuous	49.45	24.04	5.00	95.00
Landowner	1 if respondent owns forest, croplands or home garden, 0 otherwise	0.59	0.49	0	1
High education	1 if the respondent has a university or polytechnic education, 0 otherwise	0.30	0.46	0	1
Taxpayer responsibility	Factor score based on nine measures of stakeholder responsibilities in conservation <sup>a</sup>	0	1	-3.38	2.30
Citizen responsibility	Factor score based on nine measures of stakeholder responsibilities in conservation <sup>a</sup>	0	1	-3.38	2.28
Farmer responsibility	Factor score based on nine measures of stakeholder responsibilities in conservation <sup>a</sup>	0	1	-3.12	2.88
Familiarity	The familiarity of native breeds and varieties to the respondent (1 has not heard of, 2 has heard of, 3 has used/tried/experience with)	2.03	0.42	1	3
Importance	The importance of preserving native breeds and varieties (4 very important – 1 not at all important)	3.09	0.71	1	4

<sup>a</sup>A detailed description of these variables can be found in Tienhaara et al. (2015)

Table 5. Logit model results for the use of information

<b>Variable</b>	<b>Coefficient</b>	<b>Standard error</b>	<b>Odds ratio</b>
Constant	0.752*	0.456	2.121
Gender (male)	-0.730***	0.127	0.482
Age	0.014***	0.005	1.014
Income	0.050	0.136	1.052
Landowner	0.030	0.127	1.031
High education	0.050	0.136	1.052
Taxpayer responsibility	0.286***	0.063	1.332
Consumer responsibility	0.074	0.068	1.077
Farmer responsibility	-0.278***	0.061	0.757
Familiarity	-0.292*	0.168	0.747
Importance	0.051	0.096	1.052
N	1354		
Nagelkerke R <sup>2</sup>	0.089		
Correct predictions	68%		

Variables are significant at the \*\*\*1%, \*\*5%, and \*10% levels.

Table 6. Results of the random parameter mixed logit (RP-MXL) models: the effects of accessing information on the respondents' preferences and scale (standard errors in parentheses)

Variable	RP-MXL Model 1		RP-MXL Model 2			RP-MXL Model 3			
	Mean	Standard deviation	Mean	Interaction with 'information accessed'	Standard deviation	Mean 'information not accessed'	Standard deviation 'information not accessed'	Mean 'information accessed'	Standard deviation 'information accessed'
ASC (status quo)	-4.4850*** (0.4070)	5.5511*** (0.5318)	-3.1538*** (0.5112)	-3.3454*** (0.6496)	6.2380*** (0.6312)	-3.5692*** (0.6337)	7.3236*** (0.9922)	-6.1497*** (0.5288)	5.7934*** (0.6743)
Food plants banked 300 -> 400	-0.0532 (0.0752)	0.8983*** (0.1439)	-0.0443 (0.1490)	-0.0214 (0.1792)	1.0910*** (0.1839)	0.0327 (0.1647)	0.6261*** (0.2589)	-0.1093 (0.1124)	1.2196*** (0.2194)
Food plants banked 300 -> 500	-0.0328 (0.0777)	0.3971*** (0.1237)	-0.0842 (0.1572)	0.0607 (0.1822)	0.5671*** (0.1850)	-0.0870 (0.1927)	0.9331*** (0.2776)	-0.1069 (0.1156)	0.9196*** (0.1925)
Food plants on farms 7 -> 1000	0.5156*** (0.0862)	1.1386*** (0.1579)	0.3205** (0.1510)	0.4896** (0.1904)	1.4330*** (0.2490)	0.5023*** (0.1866)	1.6040*** (0.3405)	0.7003*** (0.1156)	1.4205*** (0.2220)
Food plants on farms 7 -> 2000	0.4823*** (0.0805)	1.1521*** (0.1218)	0.3370** (0.1410)	0.4042** (0.1725)	1.4594*** (0.2090)	0.5346*** (0.1704)	1.4439*** (0.2371)	0.6138*** (0.1103)	1.6122*** (0.1784)
Ornamental plants banked some -> half	0.3287*** (0.0785)	0.9614*** (0.1292)	0.2776** (0.1416)	0.2014 (0.1724)	1.2273*** (0.1803)	0.3126* (0.1749)	1.5594*** (0.2663)	0.3729*** (0.1093)	1.1914*** (0.1960)
Ornamental plants banked some -> majority	0.3002*** (0.0778)	1.1419*** (0.1259)	0.2441* (0.1464)	0.1961 (0.1727)	1.4396*** (0.1734)	0.2393 (0.1864)	1.9244*** (0.2810)	0.4137*** (0.1116)	1.6473*** (0.2936)
Native horses banked	0.2399*** (0.0538)	0.6793*** (0.0920)	0.1868* (0.0983)	0.1771 (0.1182)	0.8566*** (0.1268)	0.2008 (0.1263)	1.1537*** (0.2004)	0.3204*** (0.0733)	0.8592*** (0.1529)
Native goats banked	0.1881*** (0.0505)	0.5800*** (0.1041)	0.0255 (0.0949)	0.3054*** (0.1128)	0.7017*** (0.1387)	0.1001 (0.1198)	0.9774*** (0.1778)	0.2900*** (0.0717)	0.8684*** (0.1435)
Native chickens banked	0.0755 (0.0548)	0.8949*** (0.1278)	0.0412 (0.1064)	0.0516 (0.1231)	1.1438*** (0.1678)	0.1017 (0.1356)	1.3835*** (0.2345)	0.0783 (0.0782)	1.2700*** (0.3301)
Native cattle breeds on farms 1 -> 2	0.2231*** (0.0723)	1.1389*** (0.1563)	-0.0790 (0.1346)	0.5195*** (0.1635)	1.4225*** (0.2074)	-0.0601 (0.1685)	1.6743*** (0.2635)	0.3670*** (0.1051)	1.7404*** (0.4899)
Native cattle breeds on farms 1 -> 3	0.2085*** (0.0689)	1.0317*** (0.1496)	-0.1159 (0.1302)	0.5725*** (0.1598)	1.2748*** (0.1894)	-0.0860 (0.1563)	1.4891*** (0.2562)	0.4080*** (0.0990)	1.4475*** (0.2920)
Native sheep breeds on farms 1 -> 2	0.0384 (0.0698)	1.1419*** (0.1773)	-0.0179 (0.1325)	0.1109 (0.1557)	1.5157*** (0.2404)	0.0086 (0.1672)	1.9440*** (0.3351)	0.0191 (0.1022)	1.8885*** (0.6129)
Native sheep breeds on farms 1 -> 3	0.1940*** (0.0736)	1.3742*** (0.2293)	0.1506 (0.1384)	0.1330 (0.1622)	1.7343*** (0.2819)	0.0768 (0.1731)	1.8998*** (0.3414)	0.2527** (0.1127)	2.4775*** (0.9077)

- Cost (EUR)	3.5236*** (0.4943)	16.8138** (7.8100)	2.8463*** (0.5303)	0.6695*** (0.1637)	14.4326** (6.8451)	5.3564*** (1.7819)	79.8477 (73.6185)	3.9625*** (0.4823)	12.5230*** (4.4238)
<b>Covariates of scale</b>									
'Info accessed'	0.2396** (0.0941)		-0.0551 (0.1004)						
<b>Model diagnostics</b>									
LL at convergence	-7222.80		-7172.20			-7129.67			
LL at constant(s) only	-10141.25		-10141.25			-10141.25			
McFadden's pseudo-R <sup>2</sup>	0.2878		0.2928			0.2965			
Ben-Akiva-Lerman's pseudo-R <sup>2</sup>	0.4854		0.4886			0.4944			
AIC/ <i>n</i>	1.5518		1.5443			1.5605			
BIC/ <i>n</i>	1.6545		1.6583			1.6178			
<i>n</i> (observations)	9484		9484			9484			
<i>r</i> (respondents)	1608		1608			1608			
<i>k</i> (parameters)	136		151			270			
<b>Likelihood ratio test</b>									
<b>Comparison</b>	<b>Test statistics</b>	<b>Degrees of freedom</b>	<b><i>P</i>-value</b>						
Model 1 vs. Model 2	101.1997	15	0.0000						
Model 1 vs. Model 3	176.0196	134	0.0087						
Model 2 vs. Model 3	74.8199	119	0.9995						

The variables are significant at the \*\*\*1%, \*\*5%, and \*10% levels.

ASC: alternative specific constant

Table 7. Results of the random parameter mixed logit (RP-MXL) models: the effects of accessing information on the respondents' willingness to pay (results in €, standard errors in parentheses)

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Variable	RP-MXL Model 1		RP-MXL Model 2			RP-MXL Model 3			
	Mean	Standard deviation	Mean	Interaction with 'information accessed'	Standard deviation	Mean 'information not accessed'	Standard deviation 'information not accessed'	Mean 'information accessed'	Standard deviation 'information accessed'
ASC (status quo)	-294.45*** (15.09)	318.72*** (22.31)	-233.13*** (19.95)	-99.88*** (22.32)	296.59*** (20.00)	-259.61*** (10.04)	428.74*** (25.18)	-303.52*** (22.02)	263.76*** (21.62)
Food plants banked 300 -> 400	-1.41 (4.31)	50.11*** (6.09)	5.64 (7.54)	-5.62 (8.94)	49.38*** (5.73)	3.86 (4.08)	54.88*** (4.73)	-0.94 (5.93)	51.07*** (5.42)
Food plants banked 300 -> 500	2.54 (4.27)	21.84*** (6.65)	3.39 (8.23)	-0.53 (9.48)	27.23*** (5.87)	-13.01*** (4.89)	45.92*** (7.02)	4.27 (5.40)	24.14*** (5.28)
Food plants on farms 7 -> 1000	51.19*** (5.82)	85.49*** (6.46)	35.12*** (8.29)	20.13** (8.88)	81.51*** (5.96)	56.18*** (8.52)	93.16*** (6.38)	51.42*** (6.51)	78.29*** (6.41)
Food plants on farms 7 -> 2000	43.49*** (5.61)	91.27*** (6.31)	38.20*** (7.35)	11.52 (8.20)	88.98*** (6.04)	41.29*** (7.08)	102.02*** (5.13)	47.25*** (5.85)	86.15*** (6.60)
Ornamental plants banked some -> half	28.46*** (5.77)	80.57*** (6.30)	31.03*** (7.96)	1.78 (8.30)	79.94*** (6.09)	21.55*** (7.53)	118.66*** (6.95)	32.78*** (6.29)	70.11*** (6.02)
Ornamental plants banked some -> majority	26.23*** (6.08)	84.15*** (5.93)	27.58*** (8.05)	0.42 (8.53)	80.53*** (5.67)	20.76** (8.29)	127.66*** (6.10)	29.03*** (6.46)	69.80*** (6.01)
Native horses banked	19.17*** (3.76)	45.66*** (4.25)	18.60*** (6.00)	2.73 (5.71)	45.95*** (4.08)	18.13*** (5.67)	60.27*** (4.80)	22.90*** (4.25)	43.16*** (4.44)
Native goats banked	15.52*** (3.47)	34.47*** (3.88)	05.07 (5.30)	14.28*** (5.47)	33.49*** (4.02)	2.10 (5.86)	55.90*** (3.88)	20.44*** (3.72)	29.53*** (3.70)
Native chickens banked	3.21 (3.74)	40.28*** (3.27)	-2.04 (5.81)	4.42 (6.05)	42.66*** (3.62)	7.22 (5.81)	60.78*** (3.11)	2.54 (4.02)	28.10*** (3.30)
Native cattle breeds on farms 1 -> 2	22.70*** (4.84)	53.71*** (4.74)	0.83 (7.60)	26.55*** (7.92)	51.92*** (5.57)	3.77 (8.01)	92.98*** (4.21)	24.35*** (5.45)	41.07*** (3.95)
Native cattle breeds on farms 1 -> 3	20.15*** (5.15)	48.40*** (5.30)	0.17 (7.03)	27.32*** (7.65)	40.68*** (4.82)	2.39 (7.27)	75.81*** (3.39)	26.58*** (5.69)	38.45*** (4.71)
Native sheep breeds on farms 1 -> 2	6.57 (5.32)	58.57*** (5.55)	11.84 (7.82)	-3.21 (7.51)	63.78*** (5.37)	-14.35* (7.97)	93.28*** (5.22)	11.71** (5.79)	58.03*** (5.05)
Native sheep breeds on farms 1 -> 3	20.18*** (5.71)	68.58*** (5.79)	21.78** (8.55)	-0.93 (8.53)	69.95*** (5.99)	-5.42 (8.18)	109.92*** (7.05)	23.77*** (6.12)	63.83*** (5.03)

**Model diagnostics**

LL at convergence	-7364.35	-7335.16	-7129.67
LL at constant(s) only	-10141.25	-10141.25	-10141.25
McFadden's pseudo-R <sup>2</sup>	0.2738	0.2767	0.2965
Ben-Akiva-Lerman's pseudo-R <sup>2</sup>	0.4797	0.4814	0.4944
AIC/ <i>n</i>	1.5817	1.5785	1.5605
BIC/ <i>n</i>	1.6843	1.6917	1.6178
<i>n</i> (observations)	9484	9484	9484
<i>r</i> (respondents)	1608	1608	1608
<i>k</i> (parameters)	136	150	270

**Likelihood ratio test**

Comparison	Test statistics	Degrees of freedom	<i>P</i> -value
Model 1 vs. Model 2	101.1997	15	0.0000
Model 1 vs. Model 3	176.0196	134	0.0087
Model 2 vs. Model 3	74.8199	119	0.9995

The variables are significant at the \*\*\*1%, \*\*5%, and \*10% levels.

ASC: alternative specific constant.

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<sup>1</sup>The code and data for estimating the specific models presented in this study, as well as the results of the sensitivity analysis, robustness checks and alternative specifications, are available at <http://czaj.org/research/supplementary-materials>.

<sup>2</sup> The specific distributions ( $f$ ) must be assumed by the modeler; this is typically based on model fit.

<sup>3</sup> In order to ensure that the global maximum in optimization was reached, we used different optimization algorithms, derived gradients analytically, and used multiple starting points. In simulation of the log-likelihood function, we used 10,000 scrambled Sobol draws (Czajkowski and Budziński, 2019).

<sup>4</sup> The models were estimated using the DCE package, which can be used to estimate MXL models, among others. The package has been developed in Matlab and is available at <https://github.com/czaj/DCE>.

<sup>5</sup> Note that the MXL model with all parameters random and correlated accounts for unobserved scale heterogeneity (Hess and Rose, 2012).

<sup>6</sup> We also estimated the discrete choice models using familiarity and importance as controls (available at <http://czaj.org/research/supplementary-materials>). We found that including familiarity and importance as additive preference controls did not change our overall conclusions: the effects of accessing information were still very similar and significant.