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

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**Abstract**

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

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

JEL codes: Q51, Q57


Appendix materials can be accessed online at:

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

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

1. Introduction

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

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

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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**

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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**

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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

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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[1]. 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

239
$$U_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt}. \qquad [1]$$

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 $\boldsymbol{\beta}_i = f(\mathbf{b} + z_i\boldsymbol{\delta}, \Sigma)$,

247     where $\mathbf{b}$ is a vector of sample means and $\Sigma$ is a variance-covariance matrix.[2]

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

252
$$U_{ijt} = \sigma_i\mathbf{x}_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt}, \qquad [2]$$

253

254     where $\sigma_i$ is the 'scale' parameter. As the utilities are ordinal, the absolute value of utility has no

255     meaning and only differences in utilities matter (Hensher, Rose & Greene 2015). Hence, this

256     specification still represents the same preferences for individual $i$. Note that since the scale and

257     preference parameters enter the model as a multiplication, they are not separately identifiable.

258     However, this does not restrict model applicability, because utility function parameters do not have

259     an absolute scale and can only be interpreted in relation to zero and each other.

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

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

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

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

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

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

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.[3]

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.[4]

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

**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[5] 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

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

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

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

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

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

5. Discussion and conclusions

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

The logit model results suggested that respondents who had read the additional information were more likely to be female, older, and perceived the conservation of genetic resources to be the responsibility of taxpayers. The respondents who were more familiar with native animal breeds and plant varieties, and those who felt that conservation was the responsibility of farmers, were less likely to read the additional information. These results are, in part, similar to those of Hu et al. (2009), who 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.

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Table 1. Sociodemographic profile of the respondents and the population

| Sociodemographic characteristic | In the data | In the population[a] |
|---|---|---|
| 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 |

[a] *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 | **Current +** Chicken Goat Horse | **Current +** Goat |
| Native breeds on farms | Goat Horse Chicken Finnsheep Western Finncattle | **Current +** Northern Finncattle | **Current +** 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[a] | 0 | 1 | -3.38 | 2.30 |
| Citizen responsibility | Factor score based on nine measures of stakeholder responsibilities in conservation[a] | 0 | 1 | -3.38 | 2.28 |
| Farmer responsibility | Factor score based on nine measures of stakeholder responsibilities in conservation[a] | 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 |

[a] A detailed description of these variables can be found in Tienhaara et al. (2015)

Table 5. Logit model results for the use of information

| Variable | Coefficient | Standard error | Odds ratio |
|---|---|---|---|
| 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 $R^2$ | 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*** | 5.5511*** | -3.1538*** | -3.3454*** | 6.2380*** | -3.5692*** | 7.3236*** | -6.1497*** | 5.7934*** |
| | (0.4070) | (0.5318) | (0.5112) | (0.6496) | (0.6312) | (0.6337) | (0.9922) | (0.5288) | (0.6743) |
| Food plants banked 300 -> 400 | -0.0532 | 0.8983*** | -0.0443 | -0.0214 | 1.0910*** | 0.0327 | 0.6261*** | -0.1093 | 1.2196*** |
| | (0.0752) | (0.1439) | (0.1490) | (0.1792) | (0.1839) | (0.1647) | (0.2589) | (0.1124) | (0.2194) |
| Food plants banked 300 -> 500 | -0.0328 | 0.3971*** | -0.0842 | 0.0607 | 0.5671*** | -0.0870 | 0.9331*** | -0.1069 | 0.9196*** |
| | (0.0777) | (0.1237) | (0.1572) | (0.1822) | (0.1850) | (0.1927) | (0.2776) | (0.1156) | (0.1925) |
| Food plants on farms 7 -> 1000 | 0.5156*** | 1.1386*** | 0.3205** | 0.4896** | 1.4330*** | 0.5023*** | 1.6040*** | 0.7003*** | 1.4205*** |
| | (0.0862) | (0.1579) | (0.1510) | (0.1904) | (0.2490) | (0.1866) | (0.3405) | (0.1156) | (0.2220) |
| Food plants on farms 7 -> 2000 | 0.4823*** | 1.1521*** | 0.3370** | 0.4042** | 1.4594*** | 0.5346*** | 1.4439*** | 0.6138*** | 1.6122*** |
| | (0.0805) | (0.1218) | (0.1410) | (0.1725) | (0.2090) | (0.1704) | (0.2371) | (0.1103) | (0.1784) |
| Ornamental plants banked some -> half | 0.3287*** | 0.9614*** | 0.2776** | 0.2014 | 1.2273*** | 0.3126* | 1.5594*** | 0.3729*** | 1.1914*** |
| | (0.0785) | (0.1292) | (0.1416) | (0.1724) | (0.1803) | (0.1749) | (0.2663) | (0.1093) | (0.1960) |
| Ornamental plants banked some -> majority | 0.3002*** | 1.1419*** | 0.2441* | 0.1961 | 1.4396*** | 0.2393 | 1.9244*** | 0.4137*** | 1.6473*** |
| | (0.0778) | (0.1259) | (0.1464) | (0.1727) | (0.1734) | (0.1864) | (0.2810) | (0.1116) | (0.2936) |
| Native horses banked | 0.2399*** | 0.6793*** | 0.1868* | 0.1771 | 0.8566*** | 0.2008 | 1.1537*** | 0.3204*** | 0.8592*** |
| | (0.0538) | (0.0920) | (0.0983) | (0.1182) | (0.1268) | (0.1263) | (0.2004) | (0.0733) | (0.1529) |
| Native goats banked | 0.1881*** | 0.5800*** | 0.0255 | 0.3054*** | 0.7017*** | 0.1001 | 0.9774*** | 0.2900*** | 0.8684*** |
| | (0.0505) | (0.1041) | (0.0949) | (0.1128) | (0.1387) | (0.1198) | (0.1778) | (0.0717) | (0.1435) |
| Native chickens banked | 0.0755 | 0.8949*** | 0.0412 | 0.0516 | 1.1438*** | 0.1017 | 1.3835*** | 0.0783 | 1.2700*** |
| | (0.0548) | (0.1278) | (0.1064) | (0.1231) | (0.1678) | (0.1356) | (0.2345) | (0.0782) | (0.3301) |
| Native cattle breeds on farms 1 -> 2 | 0.2231*** | 1.1389*** | -0.0790 | 0.5195*** | 1.4225*** | -0.0601 | 1.6743*** | 0.3670*** | 1.7404*** |
| | (0.0723) | (0.1563) | (0.1346) | (0.1635) | (0.2074) | (0.1685) | (0.2635) | (0.1051) | (0.4899) |
| Native cattle breeds on farms 1 -> 3 | 0.2085*** | 1.0317*** | -0.1159 | 0.5725*** | 1.2748*** | -0.0860 | 1.4891*** | 0.4080*** | 1.4475*** |
| | (0.0689) | (0.1496) | (0.1302) | (0.1598) | (0.1894) | (0.1563) | (0.2562) | (0.0990) | (0.2920) |
| Native sheep breeds on farms 1 -> 2 | 0.0384 | 1.1419*** | -0.0179 | 0.1109 | 1.5157*** | 0.0086 | 1.9440*** | 0.0191 | 1.8885*** |
| | (0.0698) | (0.1773) | (0.1325) | (0.1557) | (0.2404) | (0.1672) | (0.3351) | (0.1022) | (0.6129) |
| Native sheep breeds on farms 1 -> 3 | 0.1940*** | 1.3742*** | 0.1506 | 0.1330 | 1.7343*** | 0.0768 | 1.8998*** | 0.2527** | 2.4775*** |
| | (0.0736) | (0.2293) | (0.1384) | (0.1622) | (0.2819) | (0.1731) | (0.3414) | (0.1127) | (0.9077) |

| - Cost (EUR) | 3.5236*** | 16.8138** | 2.8463*** | 0.6695*** | 14.4326** | 5.3564*** | 79.8477 | 3.9625*** | 12.5230*** |
|---|---|---|---|---|---|---|---|---|---|
|  | (0.4943) | (7.8100) | (0.5303) | (0.1637) | (6.8451) | (1.7819) | (73.6185) | (0.4823) | (4.4238) |
| **Covariates of scale** | | | | | | | | | |
| 'Info accessed' | 0.2396** | | -0.0551 | | | | | | |
|  | (0.0941) | | (0.1004) | | | | | | |
| **Model diagnostics** | | | | | | | | | |
| LL at convergence | -7222.80 | | -7172.20 | | | -7129.67 | | | |
| LL at constant(s) only | -10141.25 | | -10141.25 | | | -10141.25 | | | |
| McFadden's pseudo-R² | 0.2878 | | 0.2928 | | | 0.2965 | | | |
| Ben–Akiva–Lerman's pseudo-R² | 0.4854 | | 0.4886 | | | 0.4944 | | | |
| AIC/$n$ | 1.5518 | | 1.5443 | | | 1.5605 | | | |
| BIC/$n$ | 1.6545 | | 1.6583 | | | 1.6178 | | | |
| $n$ (observations) | 9484 | | 9484 | | | 9484 | | | |
| $r$ (respondents) | 1608 | | 1608 | | | 1608 | | | |
| $k$ (parameters) | 136 | | 151 | | | 270 | | | |

**Likelihood ratio test**

| Comparison | Test statistics | Degrees of freedom | *P*-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

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)

| 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*** | 318.72*** | -233.13*** | -99.88*** | 296.59*** | -259.61*** | 428.74*** | -303.52*** | 263.76*** |
| | (15.09) | (22.31) | (19.95) | (22.32) | (20.00) | (10.04) | (25.18) | (22.02) | (21.62) |
| Food plants banked 300 -> 400 | -1.41 | 50.11*** | 5.64 | -5.62 | 49.38*** | 3.86 | 54.88*** | -0.94 | 51.07*** |
| | (4.31) | (6.09) | (7.54) | (8.94) | (5.73) | (4.08) | (4.73) | (5.93) | (5.42) |
| Food plants banked 300 -> 500 | 2.54 | 21.84*** | 3.39 | -0.53 | 27.23*** | -13.01*** | 45.92*** | 4.27 | 24.14*** |
| | (4.27) | (6.65) | (8.23) | (9.48) | (5.87) | (4.89) | (7.02) | (5.40) | (5.28) |
| Food plants on farms 7 -> 1000 | 51.19*** | 85.49*** | 35.12*** | 20.13** | 81.51*** | 56.18*** | 93.16*** | 51.42*** | 78.29*** |
| | (5.82) | (6.46) | (8.29) | (8.88) | (5.96) | (8.52) | (6.38) | (6.51) | (6.41) |
| Food plants on farms 7 -> 2000 | 43.49*** | 91.27*** | 38.20*** | 11.52 | 88.98*** | 41.29*** | 102.02*** | 47.25*** | 86.15*** |
| | (5.61) | (6.31) | (7.35) | (8.20) | (6.04) | (7.08) | (5.13) | (5.85) | (6.60) |
| Ornamental plants banked some -> half | 28.46*** | 80.57*** | 31.03*** | 1.78 | 79.94*** | 21.55*** | 118.66*** | 32.78*** | 70.11*** |
| | (5.77) | (6.30) | (7.96) | (8.30) | (6.09) | (7.53) | (6.95) | (6.29) | (6.02) |
| Ornamental plants banked some -> majority | 26.23*** | 84.15*** | 27.58*** | 0.42 | 80.53*** | 20.76** | 127.66*** | 29.03*** | 69.80*** |
| | (6.08) | (5.93) | (8.05) | (8.53) | (5.67) | (8.29) | (6.10) | (6.46) | (6.01) |
| Native horses banked | 19.17*** | 45.66*** | 18.60*** | 2.73 | 45.95*** | 18.13*** | 60.27*** | 22.90*** | 43.16*** |
| | (3.76) | (4.25) | (6.00) | (5.71) | (4.08) | (5.67) | (4.80) | (4.25) | (4.44) |
| Native goats banked | 15.52*** | 34.47*** | 05.07 | 14.28*** | 33.49*** | 2.10 | 55.90*** | 20.44*** | 29.53*** |
| | (3.47) | (3.88) | (5.30) | (5.47) | (4.02) | (5.86) | (3.88) | (3.72) | (3.70) |
| Native chickens banked | 3.21 | 40.28*** | -2.04 | 4.42 | 42.66*** | 7.22 | 60.78*** | 2.54 | 28.10*** |
| | (3.74) | (3.27) | (5.81) | (6.05) | (3.62) | (5.81) | (3.11) | (4.02) | (3.30) |
| Native cattle breeds on farms 1 -> 2 | 22.70*** | 53.71*** | 0.83 | 26.55*** | 51.92*** | 3.77 | 92.98*** | 24.35*** | 41.07*** |
| | (4.84) | (4.74) | (7.60) | (7.92) | (5.57) | (8.01) | (4.21) | (5.45) | (3.95) |
| Native cattle breeds on farms 1 -> 3 | 20.15*** | 48.40*** | 0.17 | 27.32*** | 40.68*** | 2.39 | 75.81*** | 26.58*** | 38.45*** |
| | (5.15) | (5.30) | (7.03) | (7.65) | (4.82) | (7.27) | (3.39) | (5.69) | (4.71) |
| Native sheep breeds on farms 1 -> 2 | 6.57 | 58.57*** | 11.84 | -3.21 | 63.78*** | -14.35* | 93.28*** | 11.71** | 58.03*** |
| | (5.32) | (5.55) | (7.82) | (7.51) | (5.37) | (7.97) | (5.22) | (5.79) | (5.05) |
| Native sheep breeds on farms 1 -> 3 | 20.18*** | 68.58*** | 21.78** | -0.93 | 69.95*** | -5.42 | 109.92*** | 23.77*** | 63.83*** |
| | (5.71) | (5.79) | (8.55) | (8.53) | (5.99) | (8.18) | (7.05) | (6.12) | (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-R² | 0.2738 | 0.2767 | 0.2965 |
| Ben–Akiva–Lerman's pseudo-R² | 0.4797 | 0.4814 | 0.4944 |
| AIC/$n$ | 1.5817 | 1.5785 | 1.5605 |
| BIC/$n$ | 1.6843 | 1.6917 | 1.6178 |
| $n$ (observations) | 9484 | 9484 | 9484 |
| $r$ (respondents) | 1608 | 1608 | 1608 |
| $k$ (parameters) | 136 | 150 | 270 |

**Likelihood ratio test**

| Comparison | Test statistics | Degrees of freedom | *P*-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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[1] 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.

[2] The specific distributions $(f)$ must be assumed by the modeler; this is typically based on model fit.

[3] 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).

[4] 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.

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

[6] 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.