Public Preferences for Pasture Landscapes and the Role of Scale Heterogeneity

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Abstract

The paper investigates the influence of different model specifications for interpreting the results of discrete choice experiments when investigating heterogeneous public landscape preferences. Comparing model specifications based on the Mixed Multinomial Logit and the Generalized Multinomial Logit Model reveals that the parameter estimates appear qualitatively comparable. Still, a more in-depth investigation of the conditional estimate distributions of the sample show that parameter interactions in the Generalized Multinomial Logit Model lead to different interpretations compared to the Mixed Multinomial Logit Model. This highlights the potential impact of common model specifications in the results in landscape preference studies.

Keywords

discrete choice experiment; public landscape preferences; livestock; Mixed Multinomial Logit Model; Generalized Multinomial Mixed Logit Model

1 Introduction

In the context of agriculture and environmental protection, changes in land use and landscapes are critical issues. They are also discussed in the context of related political actions. Here, one important topic is the development of pasture land and the way it is utilized by agriculture (SCHAAK and MUSSHOFF, 2020). Public preferences are derived by letting citizens assess and valuate the aesthetic quality of landscapes (RAMBONILAZA and DACHARY-BERNARD, 2007). A landscape can be defined as "the outdoor environment, natural or built, which can be directly perceived by a person visiting and using that environment" (HULL IV and REVELL, 1989). These preferences have been analyzed by numerous studies, reviews are for example given by ZÁKOVÁ KROUPOVÁ et al. (2016) and VAN ZANTEN et al. (2014).

The research in this field heavily relies on the usage of stated preference methods. Besides the contingent valuation method, an increasing share of studies utilize Discrete Choice Experiments (DCE) (HOYOS, 2010). DCEs (see LOUVIERE et al., 2000, for a general treatment) have the advantage that they allow for the derivation of the Willingness to Pay (WTP) for landscape changes (DE AYALA BILBAO et al., 2012). An important aspect of the analysis of DCEs is the way by which the researchers deal with heterogeneity in the preferences between individuals. Here, multiple approaches have been developed, of which most approaches are based on the Mixed Multinomial Logit Model (MIXL) (MCFADDEN and TRAIN, 2000; TRAIN, 2009). The MIXL allows for varying parameters, which are expressed by a continuous heterogeneity distribution and has been widely applied in the literature. While the MIXL allows model specifications in which the parameters are correlated, the term is commonly used for specifications with uncorrelated parameters (FIEBIG et al., 2010; HESS and TRAIN, 2017). In the present paper, MIXL refers to the latter case. Apart from the MIXL, other approaches to allow for preference heterogeneity between individuals have been proposed, e.g. models allowing individuals' preferences to be a mixture of different latent classes of preference patterns (BOXALL and ADAMOWICZ, 2002), or so-called "scale-heterogeneity", meaning to allow the scale of the idiosyncratic error (and thus the randomness of their behavior) to vary between individuals (FIEBIG et al., 2010). A model which nests both the latter approach and the MIXL is the Generalized Multinomial Model (GMNL) (FIEBIG et al., 2010).

So far, to the best of the authors' knowledge, there are currently no applications of the GMNL in the field of landscape evaluations, although DE AYALA BILBAO et al. (2012) note that "there seems to be a need for analyzing the behavior of this model in this kind of applications". The present paper aims to close this research gap. In order to achieve this, the recent

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Table 1. Characteristics of previous landscape preference studies account for livestock preference (n = 21)

Visual representations	Methodology	Species	Country	Monetary evaluation
Yes: 17 No: 4	Picture evaluation: 10 DCE: 7 Questionnaire: 1 CVM: 1 Qualitative: 1 Other: 1	Cattle: 15 Sheep: 7 Horses: 4 Not explicitly mentioned: 3 Pigs: 1	Ireland: 4 Finland: 3 Germany: 2 Portugal: 2 Netherlands: 2 Italy: 2 Spain: 2 Norway: 1 Austria: 1 Switzerland: 1	Yes: 4 No: 17

Notes: [a]some studies considered multiple animal species
Sources: literature compiled by VAN ZANTEN et al. (2014) and own literature research

study by SCHAAK and MUSSHOFF (2020), who study public preferences for pasture landscapes in Germany, is revisited. One particularity of the study is the focus on the presence of livestock in the landscape, an aspect which is particularly relevant from an agricultural perspective, but which has only rarely been explicitly considered in the landscape preference research (see Table 1)[1]. As shown in the table, only 21 studies have been carried out in the European context, and only 7 are based on DCEs. Further, to the best of the authors' knowledge, the study of SCHAAK and MUSSHOFF (2020) is the only one considering varying livestock densities.

In order to study whether preference and/or scale heterogeneity is present in the context of landscape evaluations, the results of the GMNL with the MIXL are compared. To further exploit the effects of the scale parameter on the preference structure, the distributions of the conditional means of individual parameters (FIEBIG et al., 2010; SARRIAS and DAZIANO, 2017) were also compared. Through the approach presented above, the paper contributes to the literature on model and model specification choices for the analysis of DCEs, especially in context of landscape preferences.

The remainder of this paper is structured as follows: In the second section, the DCE is described. In Section 3, first the survey design and data collection are presented. Then, the collected data is described and econometric models used for their analysis are outlined. The results are presented and discussed in section 4. The paper ends with conclusions (section 5).

2 The Experiment

In the following subsections, the study first motivates and describes the scenario, attributes, and levels of the DCE as well as the graphical representations of the choice sets of the study by SCHAAK and MUSSHOFF (2020). Thus, the elaborations closely follow the original elaborations.

2.1 Scenario, Attributes and Levels

The attributes of the DCE and their reflective levels are presented in Table 2. The attribute *presence of livestock* describes the presence and number of dairy livestock on the pasture. The different levels differentiate between no livestock, and a low, medium, or high number of livestock. *Structuredness of the pasture* is an attribute which is represented by a parceling of the grazing area. This is done by fences, which divide the pasture into additional land parcels. The different levels distinguish between no additional parcels, or a low, medium or high number of additional parcels on the main plot. Another attribute is *point landscape elements*, including trees and individual bushes. These elements are classified as either present or not present. The attribute *linear landscape elements* describes hedges and larger groups of bushes. As for the point landscape elements, these elements are either

[1] These studies are: ARNBERGER and EDER (2011); BARROSO et al. (2012); VAN BERKEL and VERBURG (2014); GRAMMATIKOPOULOU et al. (2012); HÄFNER et al. (2018); HOWLEY (2011); HOWLEY et al. (2012a, 2012b); HYNES and CAMPBELL (2011); KALTENBORN and BJERKE (2002); KOMOSSA et al. (2019); LOPEZ-RODRIGUEZ et al. (2019); NOTARO et al. (2019); POUTA et al. (2014); SCHAAK and MUSSHOFF (2020); SCHMIDT et al. (2017); SERRANO-MONTES et al. (2019); SOINI et al. (2012); SOLIVA et al. (2010); SUROVÁ and PINTO-CORREIA (2008); VECCHIATO and TEMPESTA (2013).

Table 2. Attributes and levels of the Discrete Choice Experiment

Attribute	Level
Presence of livestock (No. of cattle)	None, low, medium, high
Structuredness of the pasture (No. of land parcels)	None, low, medium, high
Point landscape elements	Not present/ Present
Linear landscape elements	Not present/ Present
Cost per household per year	€0, €15, €30, €45, €60, €75, €90

Source: SCHAAK and MUẞHOFF (2020)

present or not present. In order to include the monetary dimension, a cost attribute was included. The *cost per household per year* can take the values €0, €15, €30, €45, €60, €75, and €90. These levels were determined in accordance with the result of a pilot study (see also Section 3.1)

As the focus is on general preferences for the landscape attributes, a general scenario was chosen. In the scenario, it is outlined that societal development will lead to more homogenous landscapes with less structural elements. Additionally, the share of grazing cattle will decrease towards a very small share. Under these assumptions, it is reasonable that the typical landscape in the future will look like what is presented in the left of Figure 1. In order to slow down or even reverse this development, a new pasture protection program is to be designed. The participant now has to choose between multiple program possibilities which are designed to lead to other expected landscape structures. These programs are associated with additional costs for citizens, which are the sum of additional taxes, fees, higher product prices, etc. (JOHNSTON et al., 2015). As the goal of the DCE was to study the general WTP for landscape elements in pasture landscapes, the programs were solely introduced as a vehicle for the cost attribute. Thus, it remained unspecific during the experiment, particularly to avoid unintended assignments of the cost specific food products, which could have for example introduced unwanted associations with perceived food quality differences. The participants were informed that they will be confronted with several sets of two pictures representing the possible expected outcomes of such a policy. They were then asked to select the alternative to which they prefer. As participants often state an exaggerated WTP in hypothetical decision situations, the scenario description includes a cheap talk-script which explicitly addresses this issue (CARLSSON et al., 2005).

2.2 Graphical Representation

The attributes of the DCE, with the exception of the cost attribute, are graphically represented. The basis is an artificially created picture of a landscape (VAN ZANTEN et al., 2016) and shown in Figure 1. Using different photos taken near Hildesheim, North Central Germany, the basis picture was generated. In order to avoid potential biases due to other landscape elements (e.g. mountains) or regional particularities, the landscape was constructed in an unspecific way. The image shows a landscape in June, and is dominated by a large pasture in the fore- and middle ground with some cultivated cropland on the sides. The pasture size is approximately 10 hectares, excluding any livestock, trees or bushes. In the right-hand corner of the background-image, a small village represents the rural character of this region. Furthermore, some trees and a

Figure 1. Left side: basic landscape with all attributes at their lowest level; right side: landscape with all attributes at their highest level

Source: SCHAAK and MUSSHOFF (2020)

forest are visible within the frame. According to the final experimental designs, the various attribute levels are gradually added, whereby the basic conditions, such as light, weather conditions and/or the perspective, remain the same. The right side of Figure 1 illustrates the landscape with all attributes at their highest level. The different images were created with Adobe Photoshop CS6.

3 Material and Methods

3.1 Survey Design and Data Collection

Based on the selected attributes and levels, a DCE was designed. It is an unlabeled DCE, including two alternatives and an opt-out-alternative, which corresponds to an alternative with all attributes at the lowest level. The design of the experiment followed a sequential process. In a first small pilot study, the participants were asked to state their maximum WTP for several possible choice alternatives which were presented (similar to a series of contingent valuations). Based on the distribution of the stated WTPs, the range, respectively levels of the cost attribute were determined. Next, a D_z-efficient design, an efficient design under the assumption of no information about the true parameter values, was created (ROSE and BLIEMER, 2009). This design was the basis for a second pilot study. Based on its results, informative priors were obtained and used for the determination of a Bayesian-D-efficient design (ROSE and BLIEMER, 2009). The final DCE consisted of 12 choice sets, with a D_b-error of 0.2819 and a related S-estimate of 20.8357. The design was transferred into graphical representations. The DCE was part of an online survey. Apart from the DCE, it contained quality checks, as well as a questionnaire regarding socio-economic characteristics and environmental attitudes. More details, including the DCE and the survey instructions can be found in SCHAAK and MUSSHOFF (2020).

3.2 Sample Description

The data collection was conducted by an online-sampling company in September and October of 2017. The sample consisted of participants from Germany. By enforcing quotas, it was ensured that the participants are representative with respect to the age, household income, federal state of residence and size of the place of residence for the German population (based on information from the German federal statistical office (DESTATIS, 2017a; DESTATIS, 2017b)). In total, 475 participants completed the survey, with 449 participants being included in the study sample. The descriptive statistics of the sociodemographic characteristics is presented in Table 3.

The participants are on average 45.5 years of age. This is below the overall German mean, but corresponds with the mean of the group of the 18-69 year olds, the age span which was offered by the sampling company. Nearly half of the participants were female, 45 % of the participants being married. As previously mentioned, the household income is representative of the German population. The average household size is 2.5, ranging from 1 to 9 persons. Although 35.4 % of the participants stated a personal relationship with agriculture (such as growing up on a farm, or having farming relatives), only 2 participants were actual

Table 3. Descriptive statistics (N= 449)

	Mean	SD
Age (in years)	45.47	14.60
Gender (0 = male, 1 = female)	46.55 %	
Marital status (not married = 0, married = 1)	44.95 %	
Household size	2.45	1.21
Monthly household income		
< €1300	9.58 %	
< €1700	8.24 %	
< €2600	23.16 %	
< €3600	18.26 %	
< €5000	24.05 %	
> €5000	16.07 %	
Personal relationship with agriculture (0= no, 1= yes)	35.41 %	
Farmer (0= no, 1= yes)	0.44%	
Landscape type around the place of residence		
Coast landscapes	5.12 %	
Forest landscapes and forest dominated landscapes	27.62 %	
Richly structured cultural landscapes	13.14 %	
Open cultural landscapes	22.72 %	
Mining landscapes	1.11 %	
Urban agglomeration	30.29%	

Source: authors‘ calculation

farmers. The majority of the participants identified their local surrounding as either an area of urban agglomeration or a forest (or forest dominated) landscape (GHARADJEDAGHI et al., 2004).

3.3 Methodology

As highlighted in the introduction, the experimental data were analyzed by the means of the MIXL and the GMNL. In this section, their properties are only briefly discussed and a short reference is made to the main references. The MIXL is a generalization of the Multinomial Logit Model, which allows for individual preference parameters (MCFADDEN and TRAIN, 2000; TRAIN, 2009). The person i's random utility for alternative j and choice situation t is given by

$$U_{ijt} = \boldsymbol{x}_{ijt}^{\mathrm{T}}\boldsymbol{\beta}_i + \epsilon_{ijt}, \tag{1}$$

with $i = 1, \dots, N; j = 1, \dots, J$ and $t = 1, \dots, T_i$. The observed alternative attributes are contained in the vector $\boldsymbol{x}_{ijt}^{\mathrm{T}}$ with the dimension $K \times 1$. ϵ_{ijt} is the i.i.d. extreme value type 1 idiosyncratic error term. The parameter vector $\boldsymbol{\beta}_i$ is unobserved and assumed to vary in the population. A common assumption is that $\boldsymbol{\beta}_i$ follows a multivariate normal distribution. Under this assumption, $\boldsymbol{\beta}_i$ can be written as

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \mathbf{L}\boldsymbol{\eta}_i. \tag{2}$$

Here $\boldsymbol{\beta}$ is the mean vector and $\mathbf{L}$ the lower-triangular Cholesky factor of the covariance-matrix of the distribution of $\boldsymbol{\beta}_i$ and $\boldsymbol{\eta}_i$ follows $N(\mathbf{0}, \boldsymbol{I})$.

The MIXL is widely applied in the literature (KEANE and WASI, 2013). In order to allow for scale heterogeneity, the GMNL, generalizes the MIXL (FIEBIG et al., 2010), where

$$\boldsymbol{\beta}_i = \sigma_i\boldsymbol{\beta} + [\gamma + \sigma_i(1-\gamma)]\mathbf{L}\boldsymbol{\eta}_i. \tag{3}$$

Here, σ_i is a scale factor of the idiosyncratic error term, and varies among individuals. It is assumed to be log-normal distributed with the mean $\overline{\sigma}$ and the standard deviation τ (FIEBIG et al., 2010). Besides the mean vector $\boldsymbol{\beta}$, the variance of residual taste heterogeneity $\mathbf{L}\boldsymbol{\eta}_i$ also varies with the scale. The extent is controlled by the scalar γ. γ can take any value, and can lead to different interpretations of the model structure (KEANE and WASI, 2013). Two special cases can be identified (FIEBIG et al., 2010). First, when $\gamma = 1$, the model reduces to $\boldsymbol{\beta}_i = \sigma_i\boldsymbol{\beta} + \mathbf{L}\boldsymbol{\eta}_i$. In this case, referred to as GMNL-I, the residual taste heterogeneity is independent of the scaling factor of $\boldsymbol{\beta}$. In the second case, referred to as GMNL-II, $\gamma = 0$, thus the residual scale heterogeneity is proportional to σ_i, as the model reduces to $\boldsymbol{\beta}_i = \sigma_i(\boldsymbol{\beta} + \mathbf{L}\boldsymbol{\eta}_i)$. The interpretation of the two models is straightforward. In case of the GMNL-I, the mean parameters are scaled by an individual, random factor. In case of the GMNL-II, both the mean parameters and the taste heterogeneity are scaled. The GMNL allows to account for "extreme", "almost lexicographic" as well as more "random" preferences (FIEBIG et al., 2010). Still, it has been argued that incautious interpretations of such models can lead to incorrect conclusions about the preference structure of the respondents (DAVIS et al., 2016). Related it is emphasized that significant results of a GMNL are not a definite proof of scale heterogeneity, as the scale parameter may also capture other sources of heterogeneity (HESS and TRAIN, 2017).

All models were estimated in the WTP-space (SONNIER et al., 2007), meaning that the WTP for the attribute was directly estimated instead of ordinary preference parameters. For both models, it is possible to derive conditional estimates for each individual (SARRIAS and DAZIANO, 2017; TRAIN, 2009). The conditional expected mean for each individual in the sample was calculated and derived the posterior distribution of the estimated means. For the technical details, see SARRIAS and DAZIANO (2017).

4 Results and Discussion

The estimation results for the choice decisions are presented in Table 4. All levels were included as dummy variables. For all attributes, the baseline level was either "none" or "not present", depending on applicability. Estimations were completed using the 'gmnl'-package (SARRIAS and DAZIANO, 2017) for the software 'R' (R CORE TEAM, 2016). The models were estimated in WTP-space requiring a fixed cost-coefficient of -1, thus, the estimated mean parameters could be directly interpreted in € for each respective level. Comparing the results of the MIXL and the GMNL in terms of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indicated that the GMNL should be preferred in terms of the AIC, while MIXL should be preferred according to the BIC. This indicates that the decision to choose one of the models over the other would depend on the preference regarding the penalization of the model complexity. Still, the estimated γ of the GMNL is close to 1, which shows that the model goes towards the special case GMNL-I. Re-estimating the model

Table 4. Regression results in WTP-space

	MIXL		GMNL		GMNL-I	
Mean Parameter	Est.	SE	Est.	SE	Est.	SE
Livestock: low	81.24***	(2.63)	87.10***	(3.01)	87.12***	(2.97)
Livestock: medium	85.78***	(3.90)	90.95***	(2.20)	90.98***	(2.19)
Livestock: high	82.89***	(2.75)	81.58***	(4.78)	81.20***	(4.71)
Structuredness: low	-5.67*	(2.74)	6.34	(4.24)	6.48	(4.25)
Structuredness: medium	-4.44*	(1.99)	7.63	(4.24)	7.31	(4.02)
Structuredness: high	6.08**	(2.31)	7.52**	(2.52)	7.55**	(2.52)
Point Elements	79.85***	(2.16)	73.72***	(2.40)	73.73***	(2.42)
Linear Elements	6.02***	(1.63)	8.28***	(1.83)	8.24***	(1.76)
Cost	-1.00[a]		-1.00[a]		-1.00[a]	
SD parameter						
Livestock: low	64.63***	(3.03)	31.60***	(5.39)	30.99***	(5.33)
Livestock: medium	106.75***	(5.28)	35.99***	(9.08)	36.43***	(8.99)
Livestock: high	119.12***	(4.93)	92.70***	(14.78)	92.94***	(14.57)
Structuredness: low	33.82***	(2.81)	37.89***	(7.35)	38.26***	(7.54)
Structuredness: medium	12.41***	(2.18)	28.41***	(7.25)	29.70***	(7.11)
Structuredness: high	36.59***	(3.59)	24.14***	(6.63)	25.22***	(6.72)
Point Elements	17.95***	(2.05)	25.50***	(5.48)	25.19***	(5.64)
Linear Elements	48.50***	(3.76)	0.62	(5.19)	2.35	(5.07)
Global parameter						
τ			1.041***	(0.126)	1.031***	(0.114)
γ			1.002***	(0.160)	1.000[a]	
Model statistics						
N	5,833		5,833		5,833	
log likelihood	-4,559.67		-4,555.10		-4,554.05	
AIC	9,151.34		9,146.21		9,142.09	
BIC	9,256.81		9,264.86		9,254.15	

Notes: using 1,000 halton draws, panel structure of the data was taken into account;
* $p<0.05$, ** $p<0.01$, *** $p<0.001$; [a] : fixed parameter
Source: authors‘ calculation

with γ restricted at 1 (thus, explicitly estimating the GMNL-I) now indicates that the GMNL-I should be preferred over the MIXL and GMNL, both in terms of AIC and BIC. The results are presented in the third column. Therefore it can be concluded that the GMNL (respectively the special case GMNL-I) outperforms the more common MIXL in this study. Additionally, the significant estimate for τ indicates that scale heterogeneity is present (this also holds for the general GMNL). For completeness, a GMNL-II model was also estimated. With respect to information criteria, it falls behind all other estimated models and is therefore not presented.

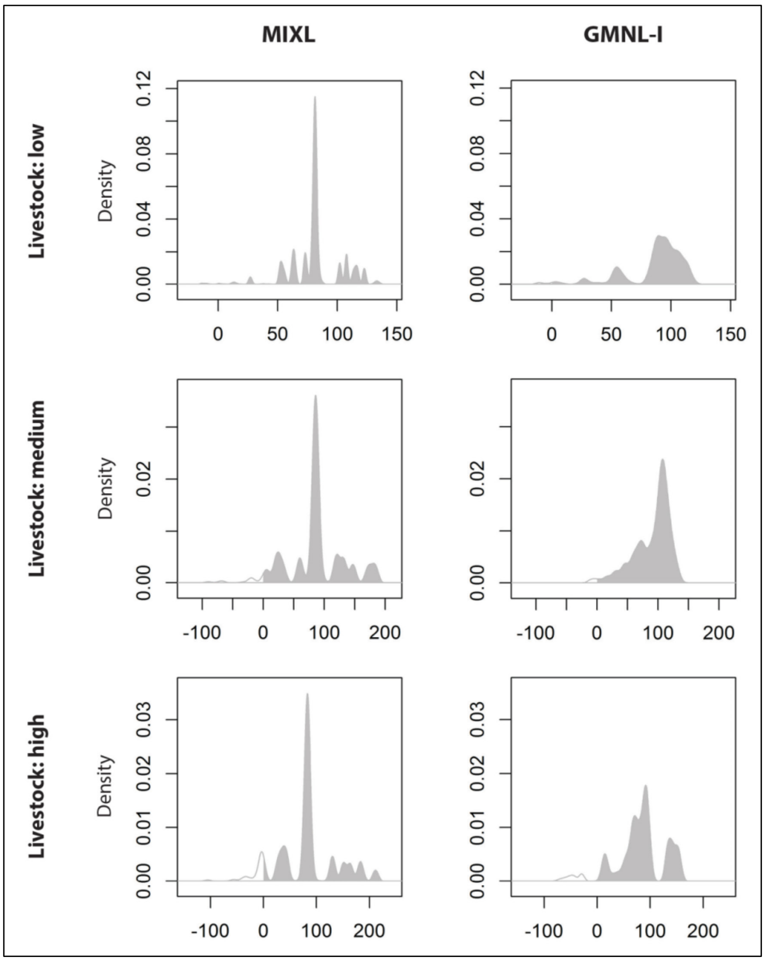
When comparing the estimates of the MIXL and the GMNL variants, it can be seen that the estimates for the mean parameters were roughly the same magnitude, while most of the estimated standard deviations distinctly changed. For the mean parameters for "Structuredness: low" and "Structuredness: medium" a sign change was observed, although only the negative values in the MIXL are statistically significantly different from zero.

Apart from the estimates for structuredness of the pasture and the statistically significant scale parameter, the results of the MIXL and the two GMNL variants appear qualitatively comparable. As previously discussed, it has been argued that researchers have to appropriately address the scale parameter in order to avoid improper conclusions. The basic implication of the significant estimate for τ indicates that the scale parameter σ_i significantly varies among the individuals in this sample, indicating that some individuals exhibit a more random choice behavior. FIEBIG et al. (2010) note that scale heterogeneity may increase with the complexity of the task. While all participants faced the same choice set in the DCE, it is reasonable to assume that the perceived complexity of the visually presented decisions situations varied between the participants. Also, the individuals may have considered more or less implications of land use change in their decisions, further influencing the individually perceived complexity. With respect to the GMNL-I, this further implies that the mean parameter vector $\boldsymbol{\beta}$ is either up- or downscaled for each individual. This serves as an explanation of the differences in the mean and standard deviation estimates between the MIXL and the GMNL-I. It also indicates that the interpretation of the estimates for $\boldsymbol{\beta}$ presented above may not be straightforward, and may have to be modified. As a result, the conditional means of the individual parameters were also calculated.

The distributions of the estimates for all attributes in both models are presented in Figures 2-4. In all figures, the left column shows the distributions for the MIXL, while the right column shows the distributions of the GMNL-I. These distributions can also be interpreted as the posterior distributions of the mean parameters (FIEBIG et al., 2010). Figure 2 presents the estimates for the livestock levels, Figure 3 presents the estimates for the structuredness of the pasture, while Figure 4 shows the linear and point landscape elements.

Two particularities can be observed in all figures. First, the distributions for the MIXL are more symmetric than the distributions from the GMNL-I. Here, most distributions are, to some degree, left-skewed. Secondly, most MIXL-distributions have more local peaks and, in case of the point and linear landscape elements, can even be described as bimodal distributions. Both aspects are particularly distinct for the livestock presence (Figure 2). In case of the medium level of livestock presence, the median value for the WTP-distribution is over €10 higher than the mean (€101.33 vs. €90.80). The distribution of the high livestock presence level also reveals that some individuals have a negative WTP for the level, which applies to 5 % of the individuals. This implies that these individuals would prefer a landscape without livestock presence over one with the highest level of present livestock. Given that the share of negative WTPs is around 1 % for the other two levels, this could indicate that some individuals consider the livestock density being too high. This could lead to issues when bringing agricultural practice and the societal preference together, as intensive rotational grazing systems require high animal densities on a particular plot.

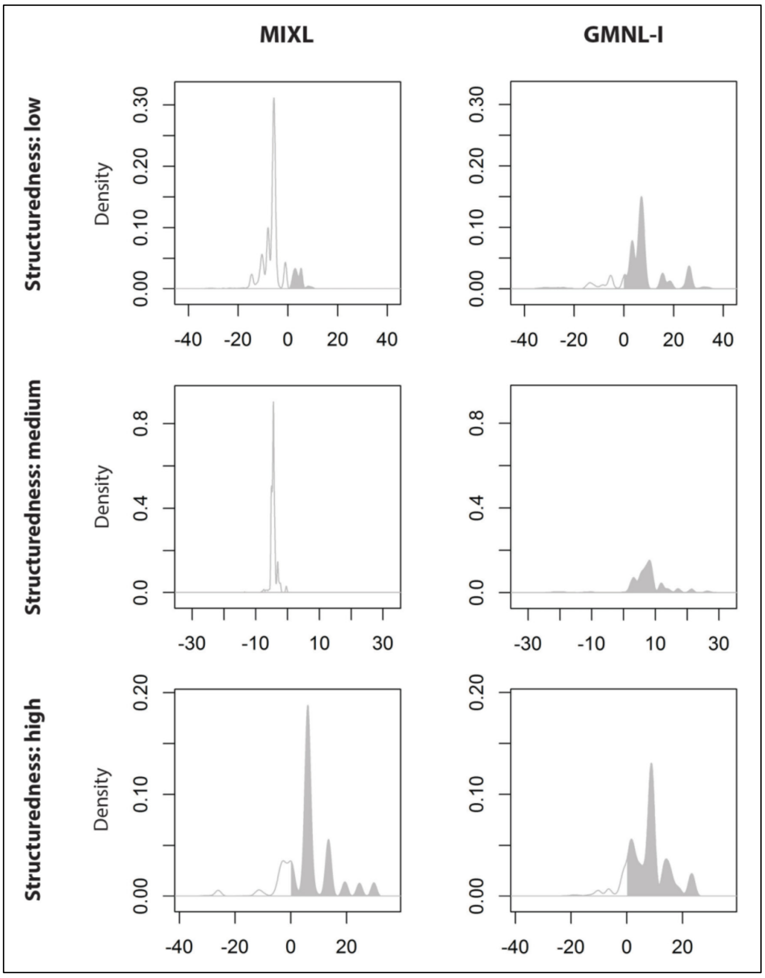
Figure 2. Distributions of the conditional WTP estimates for the livestock dummies



Notes: the grey area gives the proportion with a positive WTP.
Source: authors' illustration

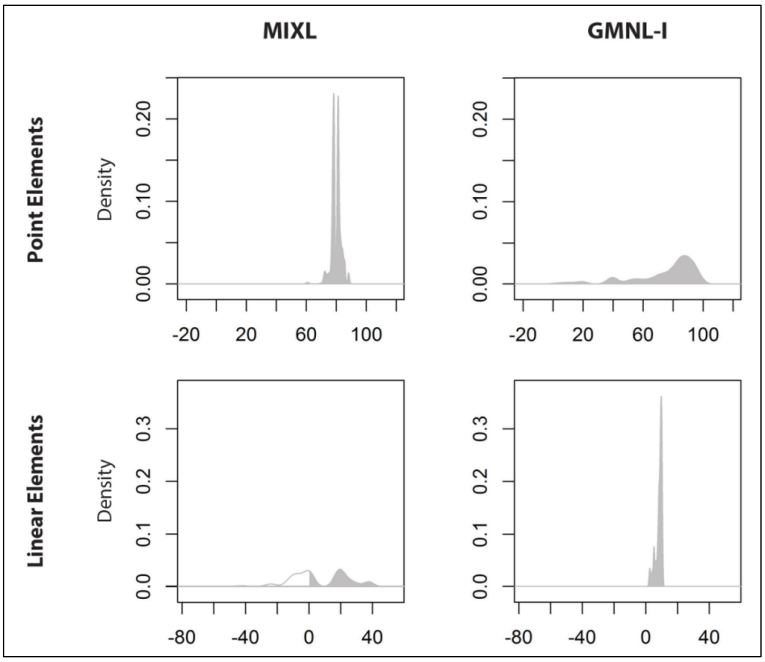
The distributions presented in Figure 3 also show the general features discussed before, but less pronounced. The differences in the share of negative WTPs have to be attributed to the differences in the estimated mean parameters of the initial models. In Figure 4, the densities of the GMNL-I are also distinctly left-skewed. Also, the densities of the MIXL feature two clear peaks. If the focus of the paper would be on the MIXL, this would also lead to interesting implications. The peaks of the linear elements are at values with different signs, and a very low density for the estimated mean parameter. This makes statements about the mean value of the population problematic, especially when being the basis for a policy recommendation. The plot for linear elements in the GMNL-I also illustrate another aspect of the GMNL. Although the estimated standard deviation is not significantly different from zero, the individual mean still follows a distribution.

Figure 3. Distributions of the conditional WTP estimates for the structuredness dummies



Notes: the grey area gives the proportion with a positive WTP.
Source: authors' illustration

Figure 4. Distributions of the conditional WTP estimates for the landscape elements dummies



Notes: the grey area gives the proportion with a positive WTP.
Source: authors' illustration

that the role of the two sources of heterogeneity can be accounted by the model.

These results show that the scale parameter can lead to distinct differences in the interpretation of the results when moving from the simple parameter estimates to the distributions of the conditional individual mean parameters. It is noteworthy that this result arises although the estimation results superficially appear qualitatively comparable. The study refrained from interpreting the results any further in terms of content, instead the reader is referred to the original study. Nevertheless, it is generally important to note that the estimated WTPs indicate that the range of the cost attribute was too narrow, which could have led to "non-trading of the cost attribute" (KJÆR, 2005) by some individuals in the sample (see also the discussion in SCHAAK and MUSSHOFF (2020)). Additionally, the unspecific construction of the cost attribute is also a potential driver of the scale heterogeneity, as the required effort for the understanding of the vehicle may have varied between individuals.

5 Conclusions

The goal of the present paper was to provide insights regarding the impact of differences of the model structure on the assessment of public landscape preferences heterogeneity when applying DCEs. In order to achieve this goal, data from a recent study by SCHAAK and MUSSHOFF (2020) was used for the application. The results show that the usage of the GMNL can be an appropriate alternative to the MIXL. Nevertheless, the results also show that the interaction of the GMNL's scale parameter can shape the conditional distribution of the individuals' means in a meaningful way and that this can be easily overlooked when only interpreting the parameter estimates.

The presented results have implications for further research. First, future studies in the field of landscape evaluation should consider whether models like the GMNL are a suitable alternative to the currently used models. Second, given the usage of such a model, the request of the theoretical literature for an explicit assessment of the estimated scale heterogeneity also applies in context landscape evaluations. Although scale heterogeneity may appear as a technical detail at first, the study has shown that addressing its implications is required when the GMNL is applied. This can potentially help to give policy recommendations which reflect different public groups with varying preferences better. Generally, when applying models that allow for individual heterogeneity, researchers should consider individual parameters' distribution rather than only the estimated means, as the posterior mean distribution is not necessarily a normal distribution, and the estimated mean parameters therefore should not be interpreted under the assumption of a normal distribution. Third, regarding the limitations of the present study, future research should incorporate sociodemographic characteristics and consider the individuals' residence in order to identify possible sources of the observed preference heterogeneity.

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