A simple method to account for spatially-different preferences in discrete choice experiments

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"The spatial dimension in analysing the linkages between agriculture, rural development and the environment"

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1. Introduction

Discrete choice experiments (DCE) are a frequently applied tool to measure welfare effects of agricultural land use changes and related policies [1]. Because there are regional differences in the way policies affect land use, and how land use change is perceived by the local population, researchers have developed methods to measure spatially differentiated welfare effects and proposed various approaches to account for spatial context in DCEs. Most prominently, individual-specific estimates served as the basis for analyzing spatial differences in marginal willingness to pay (MWTP) [2–6]. However, such approaches require strong assumptions regarding the model and the distribution of preferences across the population, resulting in highly uncertain outcomes of the spatial distribution of MWTP.

In this paper, we present an alternative approach, which we use to estimate and map spatially-different MWTP for local land use changes. We incorporate the actual status quo situation of respondents (i.e. current landscape characteristics in their proximity) in the random utility model and derive a marginal willingness to pay function with the status quo as an argument. Combining this function with spatial land use and population data allows us to predict per person and total MWTP of different spatial units such as county level. The aim is to provide a map with MWTP values on county level. As an illustrative example, we use MWTP for forest cover.

2. Sample and Survey Data

The data used in this analysis came from a web-based DCE investigating preferences for land use changes in Germany. The sample consisted of about 1,400 randomly selected

German adults recruited from an online panel of a German market research institution.[1] Besides the DCE, the questionnaire included questions on socio-demographics, attitudes and perceptions of land use and land use induced climate change. Additionally, the respondents indicated their place of residence on an embedded map from which we could extract WGS84 coordinates.

The DCE consisted of nine choice sets, with each having three alternatives. The third alternative was a generic status quo scenario, where all attributes were set to “as today”. Each alternative comprised six attributes, including a price attribute, which was framed as a yearly contribution to a local land use fund. The price for the status quo scenario was set to zero, and, for the other scenarios, ranged between 10 and 160 Euros.

The other five attributes comprised three level each of which one level represented the status quo as “as today”. The attributes related to share of forest in the landscape, the average size of fields and forests, agro-biodiversity, the share of grassland on agricultural land and the share of maize on arable land (Table 1). The DCE focused on *local* land use changes. In the instructions, we explained to the respondents that all changes would take place within a 15 km radius of their place of residence, implying different status quo situations for each respondent, and thus a different interpretation of the “as today” levels.

[Insert Table 1 here]

3. Method

Our approach consists of four steps, which we broadly define as data preparation, model estimation, willingness to pay prediction and value mapping (Figure 1).

[Insert Figure 1 here]

[1] www.link-institut.de/?lang=en; Our sample is not fully representative for income and education.

In the first step, we identified the respondents' places of residence with the WGS84 coordinates and merged the data with land use data from Corine land cover.[2] Then, we calculated the average size of fields and forest, and the share of forest, maize and grassland, each within the 15 km radius for each respondent[3]. Finally, we substituted these values into the "as today" levels of the attributes. For field size, we halved or doubled the values of the other attribute levels and for forest share, subtracted or added 10% for levels "10% less" and "10% more". For the other two attributes, the absolute level values remained.

The second step included the development of a utility function specification and estimation. As is standard practice in DCEs, we assumed a random utility function as

$$U = V + \epsilon = f(X, Z) + \epsilon \tag{1}$$

where U is utility, V is its deterministic and ϵ its unobserved part. X is a vector of attributes. The coefficients of the utility function can be estimated using discrete choice models such as logit or probit. From the utility function, we can directly derive the marginal willingness to pay function. MWTP for element n of X is calculated as

$$MWTP_n = -(f'(x_n))/\beta_{price} \tag{2}$$

where f' is the partial derivate with respect to x_n and β_{price} is the marginal utility of income. If MWTP depends on the status quo (e.g. by a logarithmic $[f(x_n) = \beta_n ln(x_n)]$ or quadratic $[f(x_n) = \beta_{n1}\, x_n + \beta_{n2}\, x_n^2]$ specification), a different status quo situation implies a different MWTP.[4]

[2] http://www.eea.europa.eu/publications/COR0-landcover
[3] We did not infer the status quo for agro-biodiversity as regional data was not available.
[4] Details on estimating discrete choice models in DCEs are given for example in Train or Louviere et al. [7,8]. Willingness to pay functions are primarily used for benefits transfer. A recent discussion is found in Rolfe et al. [9]

In the third step, we used the marginal willingness to pay function to predict MWTP for different spatial units. In this paper, we focus on German counties, the second largest administrative zones, of which 402 exist. The average per person WTP in each county depends on the distribution of the status quo within the county. For forest share, we need to know how many people have which forest share per county. We can infer it with population data in Germany. In our case, this data is in raster format on a 250x250m resolution [10]. For each raster cell, we can calculate – as in step 1 – the share of forest and how many people live in this raster cell. For simplicity, we used a discrete distribution with categories for share of forest $< 5\%;\ 5- < 10\%;\ 10- < 20\% \ldots 90- < 100\%$. Figure 2 provides an example of the distribution in the county "Golsar".

[Insert Figure 2 here]

Finally, we predicted MWTP with respect to the distribution for each outcome using the marginal willingness to pay function and calculated the weighted average within each county to obtain the average MWTP per person. Then, we multiplied this value by the eligible population in the county to obtain total MWTP. This step can be extended, for example, to predict absolute willingness to pay, i.e. for non-marginal increases. Then, one has to calculate the area under the marginal willingness to pay function between the status quo and the desired level.

The last step involved mapping the MWTP values. One can do this with any GIS software. Besides the per-person and total MWTP, one can also map the standard deviations of MWTP, absolute willingness to pay for a predefined scenario, etc.

4. Results

In this section, we demonstrate the approach for forest share.[5] We used a conditional logit specification to estimate the following random utility function, where all attributes but price, field size and biodiversity entered the utility as (inversely) U-shaped, quadratic functions.

$$\begin{aligned} U = V + \epsilon = \beta_0 ASCsq + [\beta_2 ShFor + \beta_3 ShFor^2] + \beta_4 FiSizHalf \\ + \beta_4 FiSizDouble + \beta_5 Biodiv + [\beta_6 ShMai + \beta_7 ShMai^2] \\ + [\beta_8 ShGra + \beta_9 ShGra^2] + \epsilon \end{aligned} \tag{3}$$

Field size was dummy coded and biodiversity entered utility linearly. Table 2 presents the estimation results.

[Insert Table 2 here]

All coefficients are significant, at least on a 5% level. The inversely U-shaped relationships of ShFor, ShMai, ShGra are illustrated in the upper part of Figure 3.

[Insert Figure 3 here]

With low shares of forest, utility is low, but a marginal increase increases utility strongly. The larger the share, the lower the marginal utility increase. At about 60%, the marginal utility is zero, the turning point of the utility function. From then on, utility decreases, but with increasing rates. This means, people, who have already 60% or more, perceive additional forest cover as negative.

The marginal willingness to pay (see lower part of Figure 3) given as

$$WTP_{ShFor}\ (ShFor) = -(\beta_1 + 2\beta_2\ ShFor)/\beta_{price} \tag{4}$$

[5] Due to space limitations we will not provide predictions and maps for the other attributes.

The optimal share is obtained by setting equation *2* to zero and solving for X_n .

The optimal share of maize on arable land is about 20%. The share of grassland on agricultural land has its optimum at about 30%.

In the next step we predict MWTP spatially. In this simplified case, the only determinant of willingness to pay is the status quo of the attributes. Thus, we observe high MWTP for more forest in areas with a low share of forest. As mentioned above, our spatial unit of analysis are German counties. Using equation (4), one can easily calculate the MWTP for each level of the discrete distribution of Figure 2. Taking the weighted average of the distribution gives the willingness to pay for the county. This step was repeated for all counties. Figure 4 presents the MWTP for changes in forest cover at county level. The left map serves as a reference for the current endowment of forest in each county. The map in the middle is the per person MWTP and the right map is the total MWTP for the county. The per person MWTP ranged between -0.6 and nine Euro. The weighted average MWTP on county level was 6.3 Euro, with a minimum of 2.5 Euro and a maximum of 9 Euro. MTWP was especially high at the coastal areas in the North of Germany as well as in parts of Saxony-Anhalt. In most counties, however, it lied between five to eight Euros. Total MWTP spreads between less than 500,000 Euro and more than 2 million Euro and is largest in urban areas and densely populated counties, especially in the northwestern parts of Germany. The lowest MWTP values are found in the eastern highlands in Thuringia and Bavaria.

[Insert Figure 4 here]

5. Discussion and Conclusion

So far, the status quo is the only explanatory variable for the variation in MWTP. Although we were able to identify large spatial differences across counties, there may be several other variables (socio-demographic, landscape type, attitudes) and unobserved factors that explain MWTP. To incorporate such variables, one can interact them with attributes, so that these variables will enter the marginal willingness to pay. Similarly, spatial variables such as the regional income, the landscape type, unemployment rates, can help to explain the variation in MWTP. As there may always be some leftover unobserved heterogeneity, one can use more advanced models such as mixed logit models to account for it.

In order to validate the approach further research is necessary. First of all, one may compare it to the other, in the literature proposed methods to capture spatial heterogeneity in preferences. Second, one can investigate the accuracy of the predictions, similar to what had been done in benefits transfer research. Third, one can develop concepts to incorporate unobserved preference heterogeneity in the mapping exercise. Fourth, different specifications of the utility function can help to better understand preference formation and concepts such as diminishing marginal utility or loss aversion.

Next steps would involve using the estimated values in cost-benefit and cost-effectiveness analysis. For example, a regulation may demand an increase of forest cover by 10%. With data on marginal yield locations, one can identify spots where profit loss of agricultural firms is minimized and contrast them with the utility gains of the local population. Ultimately, one can determine areas where utility gains – profit loss is maximized.

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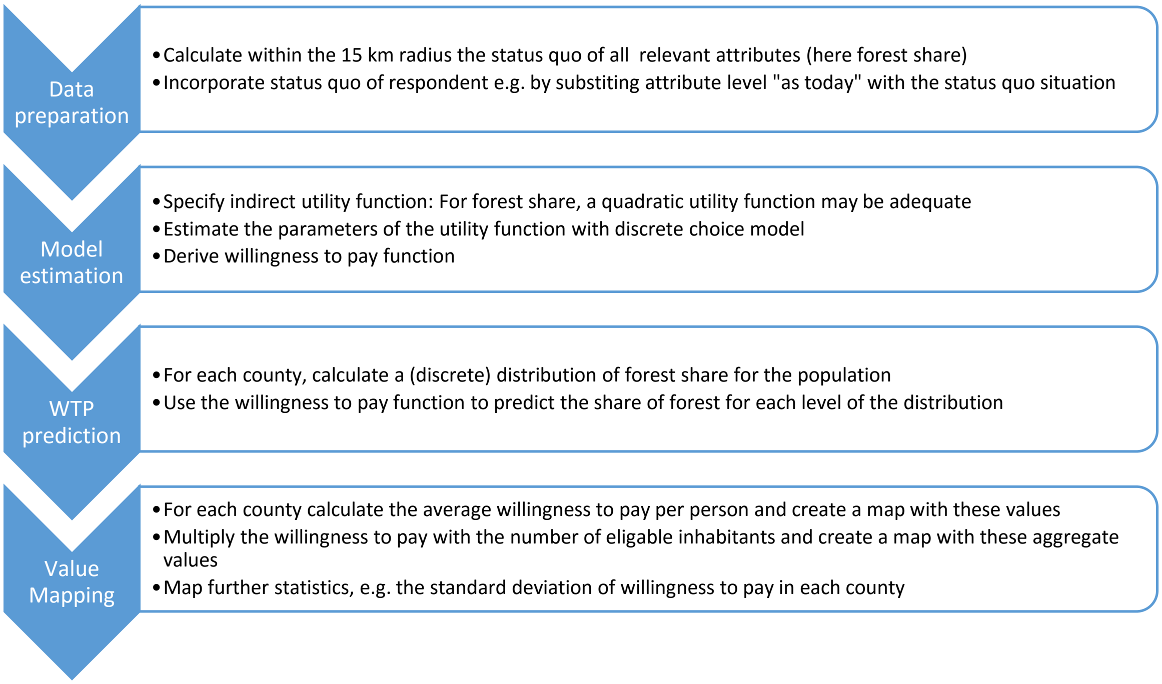

Figure 1: Required steps to estimate per person and aggregate willingness to pay for each county

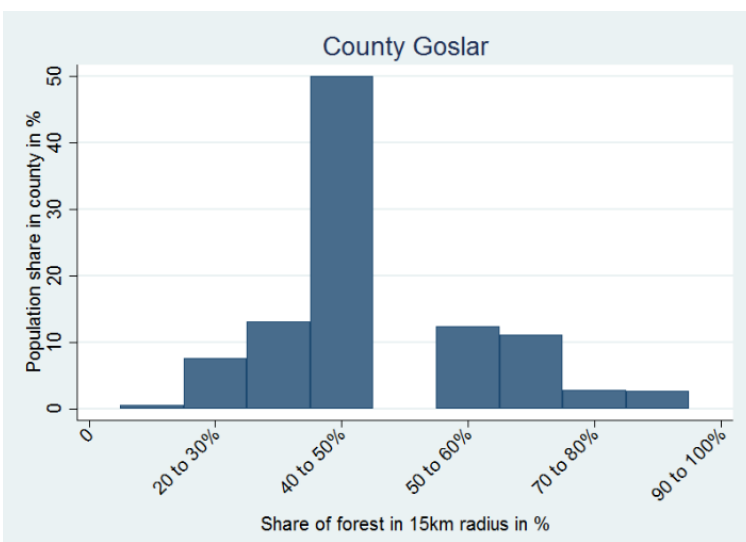

Figure 2: Distribution of the share of forest within a 15km radius in the county "Golsar"

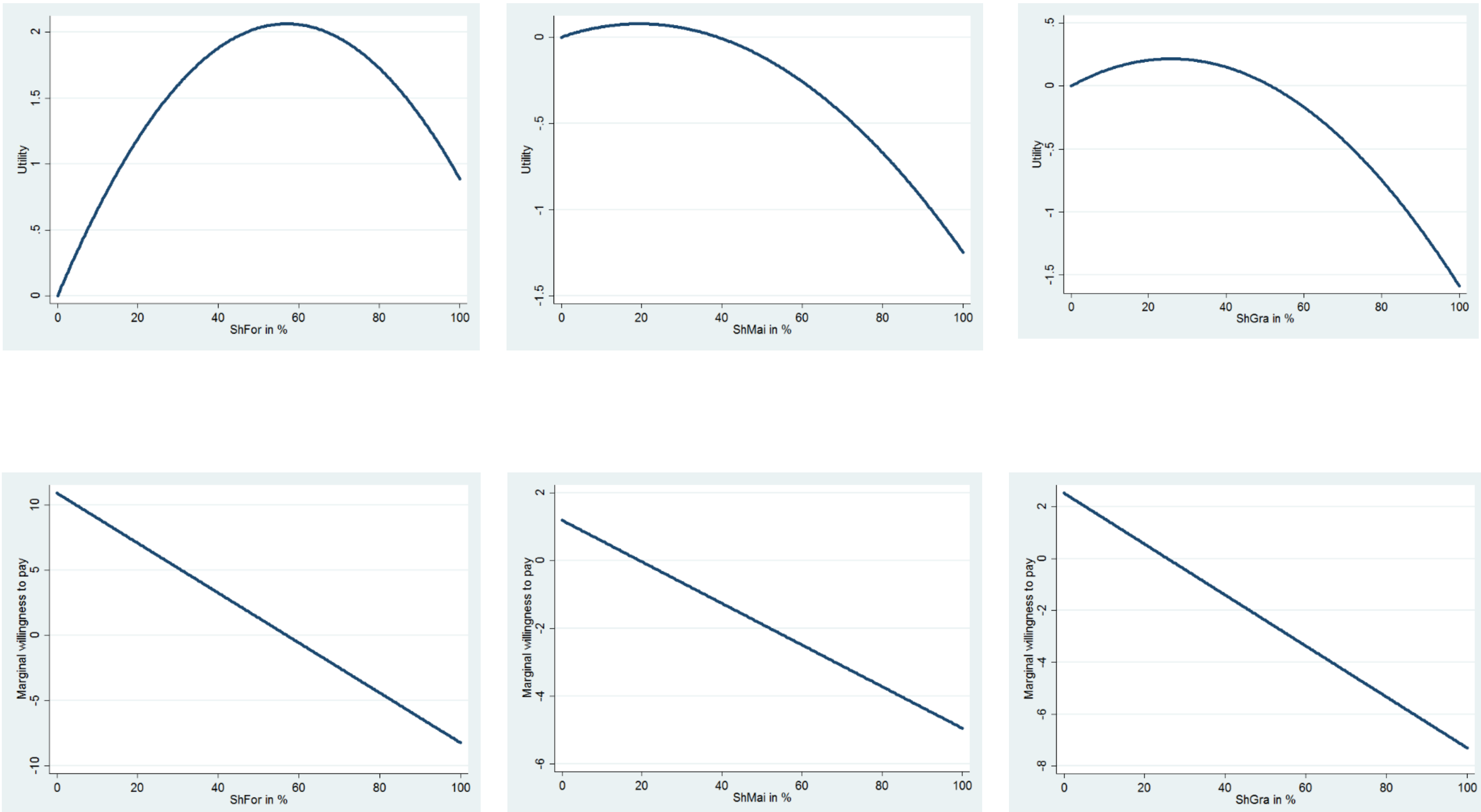

Figure 3: Utilities and marginal willingness to pay for attributes with a quadratic term

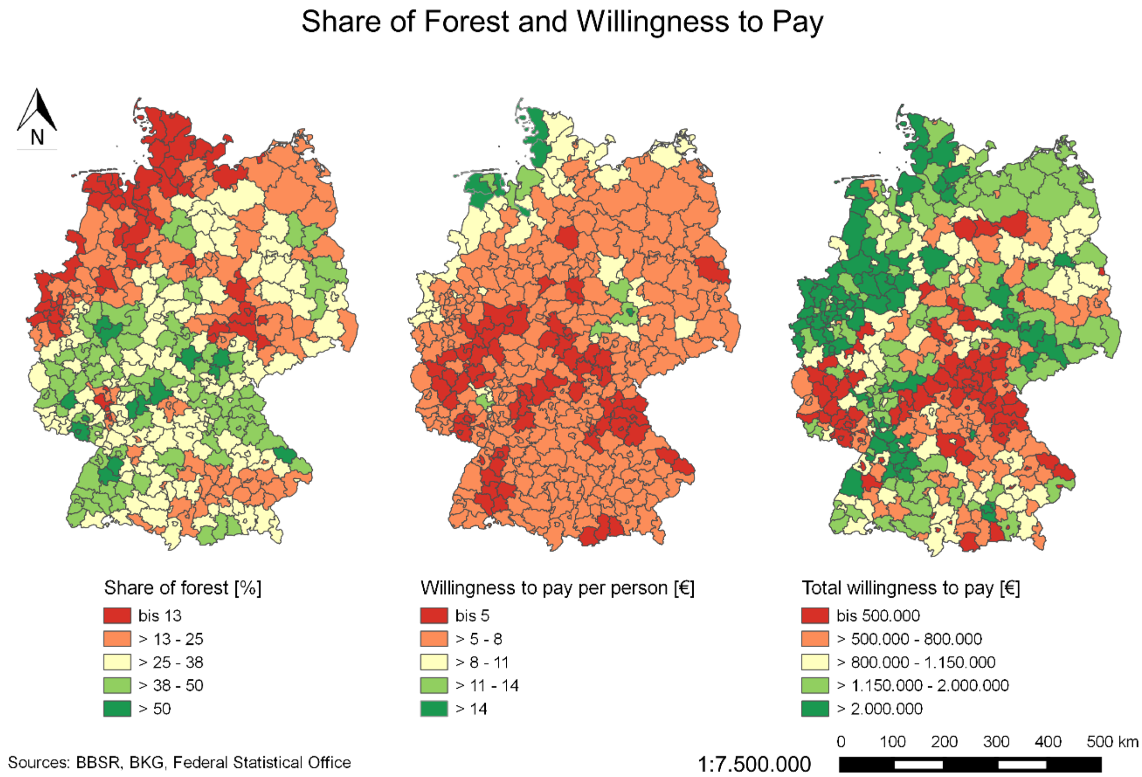

Figure 4: Share of forest, per person and total marginal willingness to pay for a 1% forest share increase, county-wise *Sources: Kleinräumige Einwohnerdisaggregation (small-scale Inhabitantdisaggregation) © BBSR Bonn 2013, Base: LOCAL © Nexiga GmbH 2013, ATKIS Basis DLM © BKG/GeoBasis-DE 2012*

Table 1: Description of attributes

Attribute	Levels
Share of forest (ShFor)	As today, decrease by 10%, increase by 10%
Field size (FiSiz)	As today, half the size, twice the size
Biodiversity in agrarian landscapes (Biodiv)	As today, slight increase (85 points), considerable increase (105 points)
Share of maize on arable land (ShMai)	As today, max. 30% of fields, max. 70% of fields
Share of grassland on agricultural fields (ShGra)	As today, 25%, 50%
Annual contribution to fund (Price)	0, 10, 25, 50, 80, 110, 160 €

Table 2: Conditional Logit Model Results

	Coefficient	Standard error
ASCsq	0.180***	0.0490
ShFor	0.0725***	0.00397
ShFor^2	-0.000636***	0.0000842
FiSiz: Half	-0.239***	0.0440
FiSiz: Double	-0.207***	0.0375
Biodiv	0.179***	0.0196

ShMai	0.00795***	0.00296
ShMai^2	-0.000204***	0.0000364
ShGra	0.0169***	0.00378
ShGra^2	-0.000327***	0.0000671
Price	-0.00666***	0.000397
Observations	33291	
Pseudo R^2	0.103	
AIC	21890.5	
BIC	21983.1	
chi2	2514.1	
Lok-Lik. (Null)	-12191.3	
Log-Lik.	-10934.3	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$