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Spatially explicit demand for afforestation

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1. Introduction

Forests provide important ecosystem services, including biomass, recreation and climate regulation. This is reflected in the new EU Forest Strategy, which emphasizes the need for multi-functional forest management to safeguard the demand for ecosystem service provision (EC, 2013). The area of forest cover has increased in Europe over the past decades (FAO, 2010) but further extending forest cover remains part of national forest strategies within the EU. Afforestation can facilitate transitions to a bio-based economy, is a cost-effective means to contribute to climate change mitigation (e.g. Valatin and Price, 2014), and can result in synergies with efforts to achieve national biodiversity conservation targets. Additionally, forests are widely used for recreational activities. The German Forest Strategy 2020 recommends the extension of forest area where afforestation can make a positive contribution to climate change mitigation, nature and landscape (BMELV, 2011). The Forest Strategy emphasizes that afforestation should take place “where possible”, depending on “regional possibilities” (*ibid*, p. 23). This implies a need for an understanding of how costs and benefits of increasing forest cover vary across the country to enable policy makers to develop efficient and regionally targeted policies based on the strategic objectives.

Some costs and benefits may be more readily observable by drawing on market information. This includes, for example, the opportunity costs of farmers who provide agricultural land for afforestation or the potential values of carbon sequestration (Yemshanov et al., 2005). However, non-market benefits to the local population arising, for example, from increased recreational possibilities and landscape aesthetics may

represent a considerable share of overall costs and benefits, which are often ignored. These additional values can be critical to determine whether an afforestation program is financially viable or whether multiple purposes (e.g. recreation, biodiversity) of afforestation can be achieved simultaneously (Gimona and Horst, 2007). Many studies also emphasize the importance of spatial heterogeneity in costs and benefits of afforestation for policy planning purposes (Broch et al., 2013; Gimona and van der Horst, 2007; Plantinga and Wu, 2003).

The environmental benefits of afforestation are well understood (Plantinga and Wu, 2003), but in contrast to the benefits from changes of forest management (see, for example Giergiczny et al. (2015) or the studies used in two recent meta-analyses by Hjerpe et al. (2015) and Barrio and Loureiro (2010)) only a few studies have investigated the non-market benefits of afforestation with stated preferences methods. Colombo and Hanley (2008) investigated marginal willingness to pay (MWTP) for increases in mixed and broadleaved woodland and found values of around 0.6 Euro for a 1% increase. Upton et al. (2012) estimated MWTP for increases in forest area in Ireland, which is characterized by low forest cover. One important finding was that the location, i.e. where the afforestation takes place, impacts MWTP. In a case study in the Basque Country in Spain, de Ayala et al. (2015) find that respondents are on average willing to pay one Euro per year for a one per cent increase in native forest area. In a case study on the Venice hinterland in Italy, Vecchiato and Tempesta (2013) report that people, on average, are willing to pay up to 50 Euro per year and household for an afforestation program, which leads to a forest share of 75% of the landscape. They emphasize that a landscape solely covered by forest is suboptimal. Further, they identify distance decay effects, i.e. the farther people live away from the hinterland, where the afforestation should take place, the lower is their MWTP.

The present study adds to the scant body of literature on non-market benefits of afforestation programs by providing insights into MWTP of private households for local afforestation in Germany. The aim is to derive spatially explicit estimates for the demand for increased forest cover across Germany. The approach taken makes use of stated preference data from a discrete choice experiment (DCE) study on local land use changes in Germany. The DCE was part of a cost-benefit analysis within a research project on climate change and land use interactions and included increases and decreases in forest share as one of the attributes. The remaining attributes were used to describe other land uses of interest and biodiversity outcomes. In this paper, we focus on the forest share attribute to examine the spatial distribution of willingness to pay for changes in forest cover and propose a novel method to derive spatially explicit MWTP values.

Two features distinguish this work from earlier studies on forest-related land use changes. The first aspect concerns the incorporation of the actual status quo of forest share each respondent faces in the status quo alternative. We argue that the assumption of constant marginal utility implied by a linear specification of the utility function may be inappropriate if the land use type is frequently used for recreational activities, which is the case for forest areas: a greater level of current supply implies a greater availability of areas that can act as substitutes to the expanded area of a land use type. This would be expected to have a negative effect on the marginal value placed upon additional units of the land use type. Additionally, a varied portfolio of land use types may be preferred over landscapes in which a single land use dominates (van Zanten et al., 2014; Vecchiato and Tempesta, 2013). In this case, an increase in a single land use type would yield additional benefits only up to a threshold, where MWTP equals zero thus representing the land use type's optimal share. Beyond the threshold, marginal benefits of additional supply decrease. One example of evidence for aversion against monotone (closed or open)

landscapes is provided by Schmitz et al. (2003), who used a DCE to value multi-functionality of landscapes in Hesse, Germany. One of their attributes referred to landscape appearance. The study finds that landscapes with moderate forest shares were preferred to landscapes with very high or very low shares of forest.

The second differentiating aspect of this study is the use of the estimated MWTP function, which depends on the status quo and other spatial variables, to predict MWTP at the county level. We thus derive a map displaying MWTP values based on individual predictions aggregated at the county level. Here, our approach contributes to the ongoing discussion on how to incorporate spatial elements in DCEs. Early approaches assume that MWTP is a function of the distance to the site that is to be valued (Schaafsma et al., 2013, 2012). However, this approach is not meaningful in the context of this study, which aims to value local land use changes where all respondents have the same distance to the valued good at hand. Further developments make use of geostatistical methods such as spatial autocorrelation to identify local and global hotspots (Campbell et al., 2008; Johnston and Ramachandran, 2013; Meyerhoff, 2013) and spatial interpolation to create smooth maps with spatially comprehensive MWTP values (Campbell et al., 2009; Czajkowski et al., 2016; Johnston et al., 2015). These approaches rely on ‘individual-specific’ estimates of MWTP, which introduces new sources of uncertainty. In contrast, the approach presented here relies on predictions and does not require further assumptions on the distribution of MWTP. It is, thus, computationally less intensive and can be applied with simpler models such as the conditional logit model.

2. Study design and survey data

This study employs data from a survey administered to 1,233 randomly selected German adults that were recruited from an online panel of a German market research company between March and April 2013. In addition to the DCE, the survey included questions on

socio-demographics, attitudes and perceptions of land use and land use induced climate change as well as on recreational activities. Respondents indicated their place of residence on an embedded Google maps interface from which we could extract WGS84 coordinates to infer their exact place of residence.

Respondents were informed that the objective of the survey is to learn more about people's views regarding the landscape in their surroundings, which is characterized by a number of attributes. Subsequently, six attributes were introduced. Five attributes described local land use changes, while the sixth attribute was a price attribute. These attributes were (i) share of forest in the landscape, (ii) the average size of fields and forests, (iii) agro-biodiversity, (iv) the share of maize on arable land and (v) the share of grassland on agricultural land (Table 1). Each attribute had three levels. Two levels described changes compared to the current situation that would occur within a 15km radius of their place of residence, while the remaining level referred to the status quo ("as today"). The attribute *share of forest* was described as the forest share of total land cover within the 15km radius. The first level was a 10% decrease in forest share, and the second level a 10% increase. Respondents were informed that decreases and increases in forest share were associated with corresponding increases and decreases in agricultural land cover. The second attribute *field size* referred to the average size of individual forest and field plots. A large field size means that, on average, individual forest areas and fields within the 15km radius of the respondent's place of residence are large, implying a more monotonic landscape. A small field size implies a more fragmented, mosaic-like landscape. The third attribute was biodiversity of agrarian landscapes (agro-biodiversity). As biodiversity is generally difficult to measure, we used a bird species indicator (Hoffmann et al., 2007) as a proxy. The indicator describes, for different landscapes, the extent to which native birds find an adequate habitat. The indicator is normalized for the

year 1970, where its value is set to 100 points. Currently, the indicator in German agrarian landscapes takes a value of 65 points (BMUB, 2015), which we used as the status quo level¹. The other attribute levels indicated a slight increase to 85 points and a considerable increase to 105 points, i.e. a condition slightly better than in 1970. The attribute *share of maize* describes the share of arable land used for maize grown for energy production and as livestock feed. Finally, the attribute *share of grassland* among agricultural land has two levels – 25% and 50%. Note that forest share, share of maize and share of grassland are percentage values. Yet, they can vary independently. An increase in forest share does not affect the share of grassland or maize and so on. Forest share relates to the whole area of land, while maize relates only to arable land, and grassland to agricultural land. We presume that an increase of forest share will not affect the composition of agricultural land uses on arable land and on agricultural land. The price attribute was framed as an annual contribution to a local land use fund, which might not be as incentive compatible as compulsory payments such as taxes. The reason for still using this framing was that respondents were asked to value rather local changes within the 15 km surroundings of their place of residence. Tax increases for such a change in land use would not be plausible for the respondents within the context of the German tax system. However, when the payment vehicle was introduced, people were told that everybody would have to pay on a yearly basis in order to finance the preferred changes in land use, and that the money would be used exclusively to implement the changes. The price of the status quo alternative was set to zero, and otherwise ranged between €10 and €160 per year. Overall, nine choice sets with three alternatives each were presented to respondents in a randomized order. Two alternatives described outcomes of *local* land use changes that would take place within a 15km radius of their place of residence. The

¹ New data that became available only after the survey was conducted showed that the bird indicator on agricultural landscapes has further decreased to 56 points (BMUB, 2015).







third alternative was a generic status quo alternative in which land use was described to remain “as today”. Table 2 provides an example choice set from the survey.

Table 1: Attributes and levels of the choice experiment

Attribute (Label)	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: Example choice set

If only the following options were available for the future development of the landscape within a radius of up to 15 kilometers around your place of residence, which one would you choose? If you live in a large city, please consider the surrounding area of the city.

		Landscape A	Landscape B	Landscape C
	Share of forest	As today	Increase by 10%	As today
	Field size	As today	Twice the size	As today
	Biodiversity on agricultural fields	Strong increase	As today	As today
	Share of maize on arable land	max. 70% of fields	max. 30% of fields	As today
	Share of grassland on agricultural fields	25%	25%	As today
	Financial contribution to fund per year	110 €	80 €	0 €
I CHOOSE		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<input checked="" type="checkbox"/>				

The experimental design used to allocate attribute levels across alternatives was generated for a multinomial logit model using the C-error as a design criterion and used uniform priors for attribute parameters. Bayesian C-efficient designs aim at minimizing the sum of the variance of the MWTP estimates (Scarpa and Rose 2008). The value ranges for the uniform priors were taken from previous studies, and to account for uncertainty in the value of the priors we used modified latin-hypercube sampling

(ChoiceMetrics, 2012) with 1000 draws for the Bayesian simulation. The whole design comprised 18 choice sets that were divided into two blocks so that each respondent faced nine choice tasks.

3. Method

3.1. Random utility model

Our econometric approach is based on random utility theory (Louviere et al., 2006; Train, 2008). It assumes that when faced with a choice among alternatives, a utility maximizing individual chooses the alternative that yields the greatest utility. The utility function that characterizes the alternatives can be decomposed into a deterministic part V and an unobserved part ϵ .

$$U = V + \epsilon \tag{1}$$

The unobserved part follows an extreme value type I distribution function, capturing the variance not explained in V . V is a linear and additive function of $n = 1, \dots, N$ attributes X_n .

$$V = f(X) = \sum_n^N \beta_n X_n \tag{2}$$

The parameters β can be estimated with maximum likelihood, using the conditional logit model (McFadden, 1974).

It is reasonable to assume that preferences vary between people and this preference heterogeneity may be important for policy analysis. Preference heterogeneity can be integrated in two ways. First, one can integrate further explanatory variables, such as socio-demographics and spatial variables into V by forming interaction terms with the attributes. Second, the attribute parameters can be specified as random parameters, with each one being characterized by a location and a scale parameter. The underlying distribution of the random parameters represents preference heterogeneity, which cannot

be explained by the explanatory variables, and is referred to as unobserved preference heterogeneity. In our application we use a panel data random parameters logit as each respondent answered nine choice situations. A detailed explanation of random parameters logit models for panel data can be found for example in Train (2008) and Hensher and Greene (2003).

A major concern in this analysis is the specification of the deterministic part V . While in most DCE applications the relationship between utility and explanatory variables (attributes) is assumed to be linear (Tuhkanen et al., 2016), our assumptions require a different specification for the attributes expressed as percentage shares. We expect that people dislike corner solutions, i.e. shares of 0% or 100%, and obey to marginal diminishing utility (Lew and Wallmo, 2011; Powe and Bateman, 2004; Veisten et al., 2004). Specifically, we expect that people's utility increases with diminishing returns up to a certain optimal level, beyond which utility will decrease. Such a pattern can be approximated with a quadratic form of the utility function with respect to an attribute of interest X_k (Adamowicz et al., 1998; Glenk et al., 2011).

$$V = \beta_{k1}X_k + \beta_{k2}X_k^2 + \sum_n^N \beta_n X_n \quad (3)$$

The first derivative of a quadratic specification of an attribute's utility surface is not constant across the values (levels) that the attribute takes, i.e., the marginal utility depends on X_k .

$$\frac{\partial U(\cdot)}{\partial X_k} = \beta_{k1} + 2\beta_{k2}X_k \quad (4)$$

Consequently, MWTP is non-constant and depends on X_k . MWTP of attribute X_k is calculated as:

$$MWTP = -(f'(X_k))/f'(X_\$) \quad (5)$$

where f' is the partial derivative with respect to X_k and the price attribute $X_\$$, respectively. This specification allows for the estimation of different MWTP estimates

for the different levels of initial endowment of a land use attribute in the status quo situation².

3.2. Incorporating the status quo

In the choice experiment application used in this paper, each respondent is subject to an individual (unique) status quo level for the attributes. To identify the respondents' current endowment of the attributes (status quo) we make use of the coordinates provided by the respondents with respect to their places of residence, which we have collected in the survey. For each respondent, we calculate the land uses in her/his 15km radius and extract the share of forest, grassland and maize from secondary data sources. For forest share and share of grassland, we used Corine land cover data from 2006³. For the share of maize, we used data from the German Maize Committee⁴. Table 3 summarizes the status quo endowments of forest share, maize share and grassland share in the sample and compares the sample mean values to the mean values of the German landscape. The values of the sample means are lower than the German average. For example, the mean share of forest in our sample is 16%, while the average share of forest in Germany is 32%. This is not surprising, because many areas with high shares of forest and/or large forest areas are not or only sparsely inhabited.

² Other non-linear specifications may be used. The quadratic specification is a parsimonious specification allowing for the two key properties (diminishing marginal utility; negative marginal utility beyond optimum) of interest here. We tested other specifications including a cubic function. The quadratic specification performed best in terms of model fit.

³ <http://www.eea.europa.eu/publications/COR0-landcover>

⁴ <http://www.maiskomitee.de>

Table 3: Status quo shares of Forest Share, Maize Share and Grassland Share

	Description	Obs	Mean	Median	S.D.	Min	Max	German Average
Forest Share	Forest share on total area in %	1,322	15.92	13.22	13.35	0	80.04	31.97% ^a
Maize Share	Maize share on arable land in %	1,322	15.53	12.47	13.49	0	69.79	21.05% ^b
Grassland Share	Grassland share on cropland in %	1,322	8.78	5.55	10.02	0.18	73.73	27.67% ^b

a) Bundeswaldinventur: <https://bwi.info/inhalt1.aspx>

b) Destatis: Landwirtschaftliche Betriebe, Fläche: Deutschland, Jahre, Bodennutzungsarten (Code: 41141-0001) <https://www-genesis.destatis.de/genesis/online>

To prepare the data set for analysis, the observed status quo needs to be incorporated into the choice model. This is done by recoding the “as today” level of the attributes of interest in the data set to the individual status quo observed for each respondent. The other attribute levels, if applicable, are adjusted relative to each individual’s status quo. For example, 10% was subtracted from or added to the individual-specific status quo to define the levels of the forest share attribute. The levels of share of grassland and maize were not described in terms of relative change but in absolute values (30% and 70% for maize, 25% and 50% for grassland), making further adjustment for these levels unnecessary. The coding for field size and biodiversity attributes remains unchanged, because data on the status quo relative to respondents’ place of residence was unavailable. Not incorporating the status quo into these attributes is not an issue for the purpose of our analysis, which focuses on the share of forest. Table 4 summarizes the attribute coding and exemplifies it for two hypothetical cases of respondents with status quo shares of forest, maize and grassland of 20% and 80%, respectively.

Table 4: Coding of attributes adapted to status quo level

Level	Field Size^a	Forest Share		Biodiversity	Share of maize		Share of grassland	
Example Status Quo	--	20%	80%	--	20%	80%	20%	80%
0	as today	20%	80%	65 points (as today)	20%	80%	20%	80%
1	half	10%	70%	85 points	30%	30%	25%	25%
2	double	30%	90%	105 points	70%	70%	50%	50%

a) Field size was dummy coded with “as today” being the reference category

3.3. Model specification

In order to capture unobserved preference heterogeneity, we estimate a random parameters logit (RPL) model for panel data with all attributes specified as random, following a normal distribution, except for price, which we assumed to be log-normally distributed⁵. Forest share, maize share and grassland share entered in a quadratic form following equation (3). The price attribute enters the utility function linearly. To capture observed preference heterogeneity in price, an interaction term of the price attribute with the average disposable income (DisInc) of the county the respondent lives in is added. The disposable income is the personal income that is available to an individual for consumption or savings. It excludes taxes and statutory insurances but includes social benefit transfers. The county average can be interpreted as an indicator of how wealthy the county is. In counties with high average disposable income, the overall infrastructure, including recreational infrastructure and landscape elements, is more developed and more substitutes for recreation are likely to be available. We therefore expect that respondents in counties with a higher regional disposable income are willing to pay less for *additional* landscape improvements.

In the model, we include an alternative specific constant (ASC_{sq}), which takes the value one for the status quo alternative and zero otherwise. The ASC_{sq} captures status quo effects, i.e., a tendency to choose the status quo alternative regardless of the levels of attributes in the other alternatives. The resulting specification of the deterministic part of the utility function used in the analysis is:

⁵ A log-normal distribution allows only positive parameter values. As the cost parameter is expected to be negative (higher costs reduce utility), we multiplied *Price* by -1. The estimated parameters for the log-normal distribution are the location and scale parameters, rather than the mean and standard deviation. Based on the estimated parameters, one can calculate mean, median and standard deviation. Thus, a negative location parameter does not imply a negative effect of the attribute on the probability to choose an alternative.

$$V = \beta_0 ASCsq + [\beta_1 ShFor + \beta_2 ShFor^2] + [\beta_3 ShMai + \beta_4 ShMai^2] + [\beta_5 ShGra + \beta_6 ShGra^2] + \beta_7 FiSizHalf + \beta_8 FiSizDouble + \beta_9 Biodiv + \beta_{10} Price + \beta_{11} PricexDisInc + \epsilon \quad (6)$$

In order to calculate MWTP, we use the median value for the log-normally distributed price coefficient rather than the mean. The median is more robust to extreme values (Bliemer and Rose, 2013) and consistent with the estimated price coefficient in the conditional logit and a RPL with a fixed price coefficient⁶. The median value of a log-normal distribution is calculated as $exp(\mu)$, where μ is the location parameter. The median MWTP for share of forest in relation to the observed status quo is calculated as:

$$MWTP_{ShFor}(SQ_{ShFor}, DisInc) = -(\beta_1 + 2\beta_2 SQ_{ShFor}) / (-exp(\beta_{10}) + \beta_{11} * DisInc), \quad (7)$$

where SQ_{ShFor} is the current share of forest within a radius of 15km from a respondents' place of residence derived as described above. Additionally, $DisInc$ impacts MWTP. For a negative sign of β_{11} , and all else equal, MWTP is lower if $DisInc$ is higher.⁷ By setting $\beta_1 + 2\beta_2 SQ_{ShFor}$ to zero and solving for SQ_{ShFor} , an estimate of the optimal share of forest based on respondents' preferences can be obtained, i.e., the point at which the marginal benefits of an additional increase in forest share are zero.

3.4. Spatial analysis

To predict MWTP for spatial units, we use the estimated parameters of equation (6) and substitute them into the MWTP function (7). The approach can be applied to any spatial

⁶ Model results are available from the authors upon request.

⁷ The approach is somewhat similar to deriving willingness to pay functions as used in benefit transfer. For a recent discussion in the context of benefit transfer, see Rolfe et al. (2015).

scale of choice. In this paper, we focus on German counties as the selected spatial unit, and predict MWTP for increases in forest share for each of the 402 counties. In the interlinked multilevel structure of German landscape planning instruments, counties participate in the second tier responsible for developing landscape structure plans (*Landschaftsrahmenpläne*).

The first step in the spatial analysis involves inference of the distribution of the population with respect to forest share. To do so, we use GIS data of the population, which is available for Germany in raster format with a 250x250m resolution (Burgdorf, 2010). This data gives, for each raster cell, the number of inhabitants. The data can then be merged with the land use data: for the centroid of each raster cell, we calculate the distribution of land use types within the 15km radius and the forest share within this area. We therefore obtain the distribution of forest share with respect to the number of inhabitants. To infer the distribution of forest share for each county, we simply extract this distribution on county level. For simplicity, we use a discrete distribution by forming categories for forest share (< 5%; 5%– < 10%; 10%–< 20%... 90%–< 100%) and sort each raster cell into the categories. We count the population within each category and divide it by the total population in the county to obtain the distribution of the status quo levels of the forest share attribute within each county. For example, a county with 100 raster cells may include 20 cells with a forest share with less than 5%. The total number of inhabitants in these 20 cells is 1,000 and the total number of inhabitants in the county is 10,000; the percentage value for the first category is, thus, 10%. Figure 1 illustrates this distribution for share of forest in two counties in Germany – Goslar, a rather forest rich county in central Germany, and Dithmarschen, in the north of Germany with low forest cover.

In the next step, we use the estimated MWTP function to predict MWTP for each forest share category following equation (7). We use the midpoint of each category (e.g., 15% for 10%–< 20%) as the value of SQ_{ShFor} and calculate the weighted average MWTP per person for each county.

$$Average\ MWTP_{county} = \sum PS_i * MWTP_i \quad (8)$$

where the index i denotes the i^{th} category of forest share and PS_i its population share.

Note that the MWTP depends on the disposable income of the county. Counties with similar distributions of forest share may therefore differ in their average MWTP values.

To obtain aggregate values of MWTP per county, we multiply MWTP per person by the number of inhabitants in each county. This step can be extended, for example, to predict absolute willingness to pay for a land use scenario, i.e., calculating the area under the MWTP function between the status quo and the desired level. To illustrate the results for per person MWTP and total MWTP, we map the estimated values.

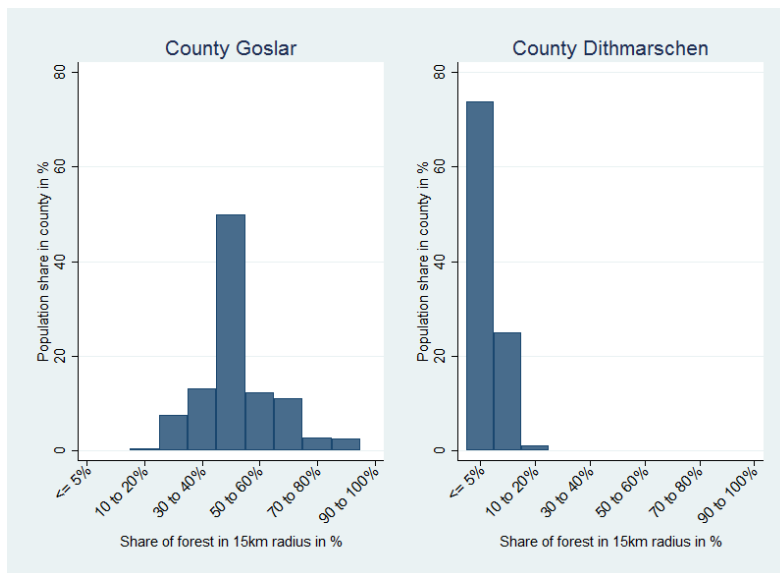


Figure 1: Distribution of the share of forest within a 15km radius in the counties Goslar (left) and Dithmarschen (right)

4. Results

4.1. Descriptive statistics

In this section we present key statistics of socio-demographic variables and compare them to the German average (Table 5). Our sample significantly differs from the German average in terms of age, sex, household size and education, as the null hypotheses of equal means or medians are rejected. Our respondents are, on average, younger, more educated, and live in smaller households, and females are underrepresented⁸. We also asked about the average number of days, people spend per year in nature and how many of these days they spend within their 15km radius. The mean value lies between 61 and 100 days (category 5) of which 37 to 60 days (category 4) are spend within the 15km radius. Our respondents also provided information on landscape types they have visited in the past for recreation (Figure 2). In the question, respondents could select two out of seven landscapes. Mixed landscapes, which include forests, agricultural fields and grassland, were chosen most often (27%). Forests, open landscapes, and rivers and lakes are all equally often chosen with around 20% each. These figures point out three implications: first, the surrounding area of the respondents' places of residence is

⁸ Sample selection bias was not accounted for in the analysis. However, relevant socio-demographic variables were not found to significantly impact WTP values when included as interactions (results of the model are available from the authors upon request). Therefore, sample selection bias is unlikely to have a significantly influence on WTP estimates reported in this paper.

frequently used for recreational activities. Second, people seem to prefer mixed landscapes over monotonic landscapes. This supports our assumption regarding the quadratic form of the utility function with respect to land use attributes. Third, forests are frequently used for recreational activities, which can explain why respondents are willing to pay for increases in forest share.

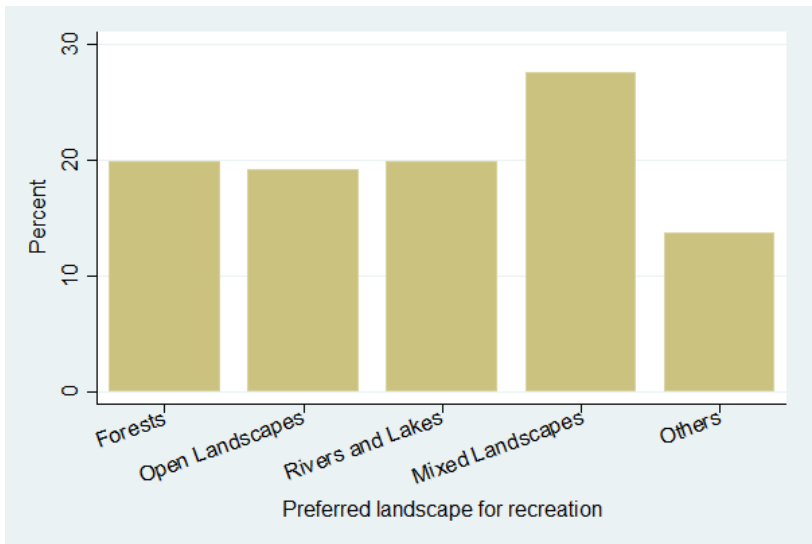


Figure 2: Respondents' preferred landscapes for recreation

Table 5: Descriptive statistics of socio-demographic variables

	Description	Obs.	Mean	Median	S.D.	Min	Max	German Average	Test of the hypothesis that sample mean equals German average; p-Value
Age	Age in years	1,233	42.70	43	14.0	18	80	50.35 ^a	Wilcoxon test p=0.00
Female	=1 if respondent is female	1,233	0.46	0	0.50	0	1	0.51 ^a	Binomial test p=0.00
Household Income	Categories for net household income (=1 if less than 900 Euros, =8 if more than 4,500 Euros)	997	6.56	7	2.06	1	10	3,132 Euros ^b	Data cannot be compared
University degree	=1 if respondent has a university degree	1,230	0.42	0	0.50	0	1	0.15 ^c	Binomial test p=0.00
Household size	Number of persons living in the household	1,233	2.55	2	1.21	1	8	2.38 ^d	Wilcoxon test p=0.00
Days in countryside	Categories for number of days/year spend in open countryside*	1,233	5.05	5	1.82	1	8	--	--
Days in countryside within 15 km	Categories for number of days/year spend in open countryside within a radius of 15km*	1,227	4.12	4	1.88	1	8	--	--

a) Destatis: Bevölkerung: Deutschland, Stichtag, Altersjahre, Nationalität/Geschlecht/Familienstand (Code: 12411-0006). <https://www-genesis.destatis.de>

b) Destatis: Einnahmen und Ausgaben privater Haushalte - Fachserie 15 Heft 4 – 2013

https://www.destatis.de/DE/Publikationen/Thematisch/EinkommenKonsumLebensbedingungen/EinkommenVerbrauch/EVS_EinnahmenAusgabenprivaterHaushalte2152604139004.pdf

c) Destatis: Bevölkerung (ab 15 Jahren): Bundesländer, Jahre, Geschlecht, Beruflicher Bildungsabschluss (Code: 12211-0041) <https://www-genesis.destatis.de>

d) Privathaushalte: Deutschland, Jahre, Haushaltsgröße (Code: 12211-0102) <https://www-genesis.destatis.de>

* Categories from 1 to 8: 1=never, 2=1 to 12 days, 3=13 to 36 days, 4=37 to 60 days 5=61 to 100 days, 6=101 to 150 days, 7= 151 to 200 days, 8=more than 200 days

4.2. Estimation results

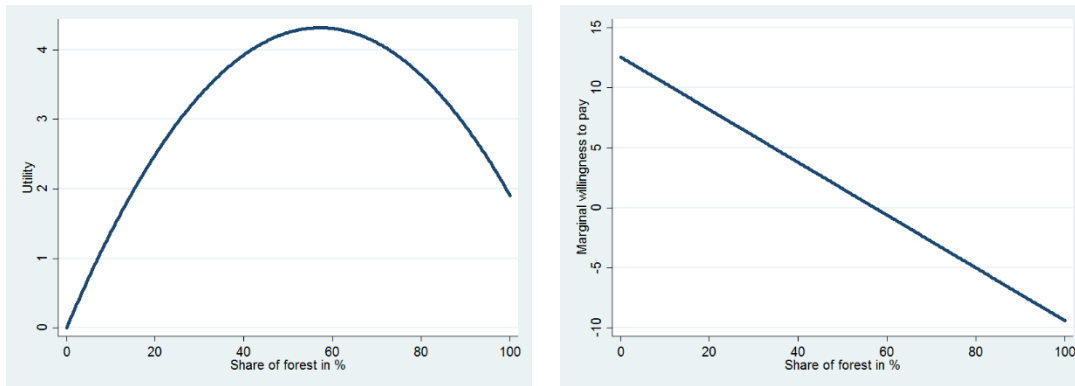
Table 6 presents the results of the RPL model. The model was estimated with Stata 14 and the user-written command ‘mixlogit’ (Hole, 2007) using 2,000 Halton draws.

Table 6: RPL model results

	Mean	Standard Deviation
ASC _{sq}	-.984 ^{***} (.146)	2.58 ^{***} (.169)
ShFor	.151 ^{***} (.01)	.103 ^{***} (.00667)
ShFor ²	-.00132 ^{***} (.000213)	6.92e-06 (.000352)
ShMai	.0101 [*] (.00611)	-.00503 (.00708)
ShMai ²	-.000313 ^{***} (.000075)	.000287 ^{***} (.0000281)
ShGra	.0221 ^{***} (.00836)	.0207 ^{***} (.00321)
ShGra ²	-.00039 ^{***} (.000144)	-.0000625 (.000173)
FiSiz: Half	-.424 ^{***} (.0811)	1.11 ^{***} (.12)
FiSiz: Double	-.385 ^{***} (.068)	.932 ^{***} (.0875)
BioDiv	.289 ^{***} (.0373)	.613 ^{***} (.0472)
Price	-4.42 ^{***} (.128)	2.75 ^{***} (.2)
Price × DisInc	-.000429 [*] (.000253)	—
Observations	33291	
AIC	15911	
BIC	16105	
χ^2	5991	
Log-Lik. (Null)	-10928	
Log-Lik.	-7933	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses

The mean coefficient for ASC_{sq} is negative and significantly different from zero at a 1% level, meaning that people, on average, prefer to move away from the status quo for reasons unrelated to the attributes. However, the parameter of the associated standard deviation is highly significant and large in magnitude relative to the mean. The linear and the quadratic terms of $ShFor$ are significantly different from zero. The linear term is positive, and the quadratic term is negative, which implies an inversely U-shaped form of utility with respect to forest share. This relationship is illustrated in Figure 3a: with low shares of forest, utility gains from increases in forest share are relatively large. With increasing forest share, marginal utility decreases. At approximately 57% forest share, marginal utility is zero, the turning point of the utility function. Beyond 57%, an additional increase in forest share is increasingly associated with a utility loss. Therefore, respondents whose forest share at present is 57% or greater perceive additional forest cover as negative. In Figure 3b, the corresponding MWTP is depicted (at mean values of disposable income). Respondents are willing to pay 12.6 Euro for a one per cent increase of forest share when the status quo endowment with forest is zero, i.e. if there is no forest within the 15km radius of the respondent. MWTP decreases and is zero at 57% forest share. Beyond 57% forest share, MWTP becomes negative. At a forest share of 100%, the MWTP is -9.3 Euro, i.e. people would pay 9.3 Euro to reduce the share by 1%. The significant standard deviation of the linear term implies that the optimal share varies among respondents.



a) b)
Figure 3: Utility (3a) and MWTP (3b) for share of forest in Euro

The linear term of *ShMai* is positive and significant on a 10% level, and the quadratic term is negative and highly significant, allowing an interpretation that is similar to the one for *ShFor*. Unlike the standard deviation of the quadratic term of *ShMai*, the standard deviation of the linear term is not significant. Both estimated parameters for *ShGra* are significant with the expected signs, also suggesting a quadratic relationship for this attribute. Both dummy variables for *FiSiz* are significant and negative, i.e. respondents neither prefer larger sizes of fields and forest nor smaller ones over the status quo. The standard deviations are also significant, i.e. there is preference heterogeneity in this attribute. *BioDiv* has a significantly positive effect on utility. More biodiversity is preferred to less, and the large and significant standard deviation parameter implies the existence of preference heterogeneity. *Price* and *DisInc* are both negative and significant. The sign of *DisInc* implies that MWTP is higher in counties with lower disposable income. The significant standard deviation (calculated on the basis of the scale parameter) of *Price* implies the presence of unobserved preference heterogeneity with respect to changes in costs to respondents.

3.5. Prediction

In this section, we predict MWTP for increases in forest share spatially for German counties. The determinants of MWTP are the status quo of forest share and the average disposable income in the county of the respondent. Therefore, we observe higher MWTP for additional forest in areas which currently have a low share of forest and in areas with lower county-average disposable income. Figure 4 presents the MWTP for changes in forest share at county level. The left map (4a) shows the current endowment of forest in each county. The map in the center (4b) is the per-person MWTP and the right map (4c) displays the total MWTP for the county. The per-person MWTP ranges between -1.48 and 14 Euro with a mean of 6.5 Euro and a standard deviation of 3.07. MWTP is especially high for the coastal areas in the North of Germany as well as in parts of Saxony-Anhalt. Total MWTP ranges between -47,573 Euro and 30.2 million Euro per county and is largest in urban areas (Berlin, Hamburg, Hannover, Munich) due to the large number of inhabitants. The lowest total MWTP values are found in the eastern highlands in Thuringia and Bavaria. The overall MWTP in Germany sums up to 487 million Euro. Note that in some counties total MWTP is negative, i.e. afforestation would have negative welfare impacts

Share of forest and marginal willingness to pay

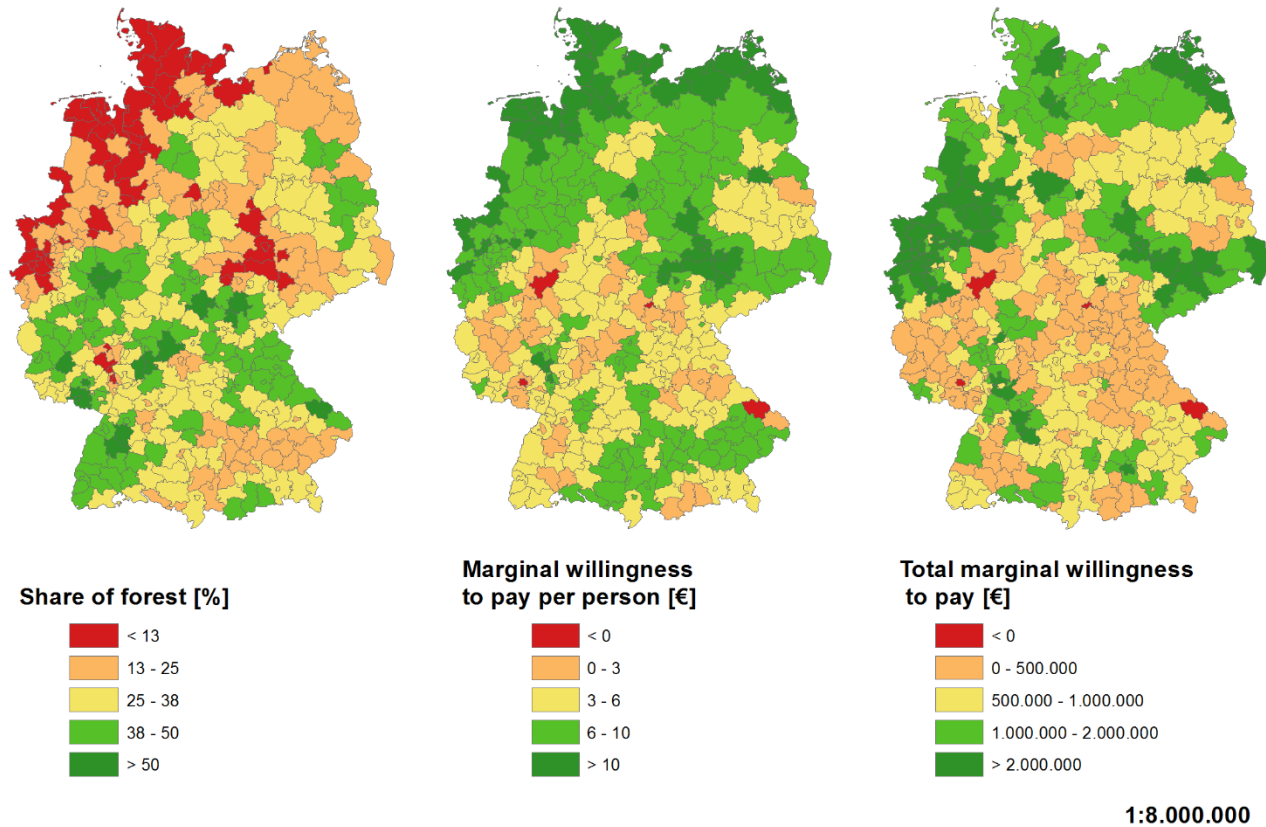


Figure 4: Share of forest (4a), per-person marginal willingness to pay (4b) and total marginal willingness to pay (4c) for a 1% forest share increase, county-wise

4. Conclusions and Policy Implications

Although afforestation is a stated goal in the European and German policy agendas, it remains unclear where the afforestation should take place. Economic analysis of costs and benefits can provide a means to inform the targeting of areas for afforestation. Such analysis may be purely based on the opportunity cost of afforestation, primarily highlighting trade-offs between afforestation and agricultural production and urban development. However, in order to base targeting decisions on where afforestation achieves the greatest benefit to society, non-market benefits of forests should be considered. These include cultural forest ecosystem services including recreation and landscape amenity, biodiversity and regulating ecosystem services. These non-market benefits can be expected to vary spatially, which is strongly confirmed by our study.

There are two main sources for this variation. First, the greater the current share of forests in the vicinity of people's place of residence, the lower is their preference for afforestation. If forest shares are very high, further afforestation can be detrimental to welfare. Second, people's marginal utility of income may vary across space. In our analysis, we accounted for both factors by incorporating the status quo forest shares and by including regional disposable income as an explanatory variable for preference heterogeneity regarding price. Our results confirm that both factors significantly impact MWTP estimates.

Our model results also show that additional preference heterogeneity exists, which we cannot explain with the variables included in the analysis. Consequently, there may be several other factors that determine WTP for afforestation, e.g., the type of forest (broadleaved trees vs. conifers) or usage (timber production vs. recreational uses). For

future research, a DCE which uses different types of afforestation as attributes could shed light on the role of such factors in explaining preference heterogeneity. Additional socio-demographic variables could have been included in our analysis to better explain preference heterogeneity and to help control for sample selection bias. However, this would also increase the requirements in GIS data and the risk of potential multicollinearity and model over-specification.

The current share of forest in Germany is about 32%, but it strongly varies across regions. While many regions in the north of Germany have very low shares of forest below 10%, some regions in the German midlands have shares larger than 50%. Specifically, our results suggest that benefits from afforestation are largest in areas with lower shares of forest and a relatively low average disposable income. In Germany, such areas are most often found in the northeastern part. This region is structurally rather poor, and an increase in forest can lead to several advantages including better quality of life and more varied recreational opportunities, which could also enhance tourism. Further analysis including opportunity costs of afforestation is needed to confirm that investment in afforestation would indeed be most efficient in these areas.

In summary, the resulting spatial distribution of MWTP has at least three implications for policy makers. First, afforestation creates significant benefits in the population which should be considered in the decision making process. Second, the location where afforestation takes place significantly affects the benefits, calling for a spatially explicit approach to comparing costs and benefits of afforestation. Third, the costs arising through afforestation could be, at least partly, recovered through local taxes or levies. For example, agri-environmental schemes to incentivize afforestation (Broch et al., 2013; Brouwer et al., 2015) could be partially financed through such charges.

German afforestation policies are the responsibility of federal states (Bundesländer) (Tietz, 2007). Each federal state has its own forest policy. Some states – Baden-Württemberg, Berlin, Brandenburg, Hamburg, Hesse, Rhineland-Palatine, Saarland – do not support afforestation at all. Some of the states with low forest shares, including Schleswig Holstein, Saxony, and Saxony-Anhalt, however, support afforestation. For example, Schleswig Holstein provides financial incentives for afforestation (MLUR, 2012) and the policy target is an increase from currently 10% to 12% of forest share (MLUR, 2008, p. 105). The policy also mentions that afforestation should take place close to urban centers, on structurally poor arable land and in areas with low forest shares. These targets are very similar to what our results suggest. However, a more centrally orientated afforestation policy would provide scope for maximizing benefits across the whole country. Policies could explicitly target areas with lower forest shares. Compensation payments could then be adapted depending on the current endowment of forests. Farmers in areas with low forest shares could be incentivized through higher compensation payments, which are more likely to exceed the opportunity costs in terms of income forgone from agricultural activity while still achieving a net benefit to society. Areas with high forest cover should be less supported, if at all.

Our approach can be readily used in benefit transfer exercises (Rolfe et al., 2015), e.g. to generate estimates for the whole European Union. Further, the analysis can be applied to smaller and larger scales, depending on the purpose of the analysis. Especially in cases where the results are used to inform local policies, a smaller scale (for example at the municipality level) is more appropriate.

There are several important caveats and limitations to the approach as presented in the paper. By applying sample median estimates of MWTP across all counties in Germany, the approach ignores that preferences are heterogeneous, as indicated by significant

standard deviation parameters in the RPL model. Further attempts could be made to explain heterogeneity in preferences through additional population or land use characteristics that are believed to systematically affect respondents' choices. The addition of average disposable income per county as a population characteristic that can be related to the investigated spatial units proved useful in this respect. However, there are limitations to adding further explanatory variables to the utility function. Irrespective of endogeneity concerns, the challenge would lie in identifying those population or land use characteristics that affect sensitivity for the attributes in the DCE. Additionally, even if a greater share of the unobserved heterogeneity could be explained, the approach is not suited to capturing more complex spatial patterns such as patchiness or hotspots of MWTP previously demonstrated in the DCE literature (Johnston and Ramachandran, 2014).

Although our results make intuitively sense and appear to be plausible, it remains unclear how the proposed approach performs in terms of accuracy. Undoubtedly, the established spatial pattern of MWTP will differ from a true representation of spatial variation in MWTP. To investigate the magnitude of error associated with the extrapolation using the proposed approach, further research should be dedicated to validate the accuracy of MWTP projections at varying spatial scales. This would require the collection of independent, representative samples at sub-national level, for example for selected counties and federal states, and subsequent convergent validity testing. Such validity testing would also be highly relevant for other approaches for spatial extrapolation of MWTP such as the combination of individual-specific MWTP estimates and kriging methods given that there is currently no information available on the magnitude of error associated with such approaches and the factors that influence their accuracy. Equally, a

cross comparison of approaches could shed some light on their performance and specific advantages and disadvantages across different contexts and scales.

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