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Exploring age and income distribution effects for willingness-to-pay to plant climate forests in Norway

Abstract

There has been an increasing interest in investigating the distributional impacts of climate policies. In the present paper, we are specifically interested in understanding how people's preferences and priorities for a carbon sequestration program in Norway differ across age and income distributions. We develop and use local conditional logit models with kernel smoothing to accommodate observed preference heterogeneity within a semi-parametric econometric framework. This framework allows us to capture non-linear preference heterogeneity without making additional assumptions about the pattern or distribution of preferences. This represents a parsimonious way to uncover observed preference heterogeneity in the presence of categorical variables with many categories. Our findings reveal that age is a key driver—while younger individuals are more likely to choose the status quo, they assign relatively higher values to mitigation policy attributes as a share of their income, which suggests that those who will receive the benefits of the program are willing to pay relatively more. We discuss the implications of the results for policy.

Keywords: climate change mitigation, climate forests, age and income distribution effects, stated choice experiment, local conditional logit model

JEL codes: C25, Q23, Q24, Q51

1 Introduction

The challenges society faces from climate change are unprecedented. To limit the impacts of climate change, the world must decarbonize its economy and do so in a cost-effective manner. Finding effective least-cost solutions can be difficult when many of the costs and benefits of policies aiming to mitigate the effects of climate change do not have market prices. Therefore, to fully evaluate the total costs and benefits of climate change mitigation and to design policies that can achieve the necessary support to be implemented, it is crucial to understand people's preferences and how these differ (Carattini et al., 2019; Douenne and Fabre, 2020; Drews and Van den Bergh, 2016; Klenert et al., 2018; Kallbekken, 2023). A particularly important aspect of climate policies, compared to other environmental policies, is the pronounced distributional effects (see, e.g., Ohlendorf et al. (2021), Mittenzwei et al. (2023), and Glomsrød et al. (2016)). Any action on climate change confronts ethical considerations of equity and responsibility across generations. The mitigation of climate change is essentially a transfer of wealth from the present generation to future generations. Across generations, the costs and benefits of mitigation are not equally shared. Younger citizens and future generations benefit from mitigation while the present generation bears the costs. Further, if the benefits or costs of climate change and climate mitigation policies are spread unevenly across different socio-economic groups within the country (or indeed, between countries), similar ethical considerations may also apply to the effects on income within the present generation. Indeed, some climate policies may excessively burden low-income members of society, for example, due to a higher share of energy and heating costs in the case of carbon taxation (Goulder et al., 2019; Berry, 2019; Burke et al., 2020; Costantini et al., 2025).

There has been an increasing interest in investigating the distributional impacts of climate policies, especially carbon taxation (e.g., Ohlendorf et al., 2021; Goulder et al., 2019; Köppl and Schratzenstaller, 2022), and in people's preferences and valuation of the benefits (and costs) of climate mitigation and their degree of policy acceptance (Dugstad et al., 2024). While some of these studies employ stated choice/stated preference methods and investigate, by use of standard econometric methods, average effects of socio-economic and other factors across the sample (e.g., Carattini et al., 2017; Gevrek and Uyduranoglu, 2015; Brannlund and Persson, 2012; Hammerle et al., 2021; Sommer et al., 2022; Svenningsen and Thorsen, 2020)[1], to our knowledge, few analyze preference heterogeneity in general or among income and age groups, specifically. Carattini et al. (2017) and Gevrek and Uyduranoglu (2015), for example, use a latent class approach to

[1] More general stated choice studies of preferences for climate and environmental policies include Andor et al. (2022) and Bergquist et al. (2020).

investigate preference heterogeneity for carbon taxation but do not examine income and age groups.

Furthermore, most studies in the growing literature on climate policy preferences and distributional aspects focus exclusively on carbon taxation (Dugstad et al., 2024). People's preferences may vary with the type of climate mitigation measure or policy, and there may be different trade-offs at play. Carbon sequestration programs, for example, may transform the landscape and affect biodiversity, which people will have to trade off against future climate mitigation effects and their concerns about the next generation (Chreptun et al., 2023; Varela et al., 2018). A recent study, not using stated choice, indicates that preferences for such programs may vary across age groups (Liu et al., 2023).

In the present paper, we are interested in understanding how people's marginal willingness-to-pay (WTP) for a forest carbon sequestration program differs across both the age and income distributions. Young people are likely to experience the effects of the program in their lifetimes, whereas older respondents are likely to only experience the costs of the program. Furthermore, older people are, on average, richer and have higher disposable incomes than younger people, which underlines the potentially skewed distribution of who pays and who benefits. This creates an interesting dynamic and a lens through which we can analyze the problem. We use data from a stated choice survey eliciting people's preferences for a carbon sequestration program involving the planting of trees on abandoned pastures in Norway, so-called climate forests. Implicit in this program is a trade-off between long-term climate mitigation benefits and more near-term negative biodiversity and landscape aesthetic effects (Aslaksen et al., 2025). This type of climate mitigation program is contentious in Norway (Grimsrud et al., 2020; Iversen et al., 2021), which makes it well-suited for studying preference heterogeneity.

We develop and use a set of local conditional logit models with kernel smoothing to accommodate observed preference heterogeneity within a semi-parametric econometric framework. We contrast this with the more traditional approach of exploring observed heterogeneity using interaction terms. While the use of such kernel-based nonparametric approaches has a long tradition in the broader field of econometrics, their use in the analysis of stated choice experiments is still limited. To our knowledge, only a handful of studies have used the proposed approach to uncover observed preference heterogeneity. These include Fosgerau (2007), Dekker et al. (2014), and Koster and Koster (2015), as well as Liu and Egan (2019) and Börger et al. (2023), who apply the approach to revealed and stated preference data. The advantage of local kernel estimators, compared to the more standard approach of using interaction terms, is that they are both intuitive and mathematically simple and result in a unique non-parametric distribution of preferences across the age and income distributions. Importantly, these models can directly uncover and handle non-linear relationships with observed characteristics, which is only possible in the standard models if we specify particular non-linear functional forms. Although the paper may initially appear to offer, primarily, a methodological or econometric contribution, it also delivers an important policy-relevant message. Specifically, we present the analysis as an application of a robust econometric framework to address a substantive environmental and social question. And, we examine how preferences for climate-change mitigation measures vary across age and income groups, thereby shedding light on issues of intergenerational equity and income distribution within climate policy. For policymakers tasked with designing effective and publicly supported mitigation strategies, understanding these heterogeneous preferences is crucial. Without such insight, policies may inadvertently privilege certain age or income groups over others. Our findings, therefore, contribute to the development of more equitable, inclusive, and politically sustainable climate policies.

The rest of the paper is organized as follows: The next section outlines the econometric approach, followed by an explanation of the design of the stated choice experiment, the data sampling strategy, and its characteristics. We then present and discuss the global and local model results before concluding the paper.

2 Model

2.1 Global model

To model the choices made by participants in the stated choice experiment, we assume that the utility, u, participant n (where $n \in \{1, 2,3, \dots, N\}$) obtains from alternative j (where $j \in \{1, 2, \dots, J\}$) in choice task t (where $t \in \{1, 2, \dots, T_n\}$) is as follows:

$$u_{njt} = v_{njt} + \varepsilon_{njt},$$

where v_{njt} is the observable part of utility, and ε_{njt} is an idiosyncratic random disturbance term. For the observable part of utility, we assume a WTP-space utility where the cost attribute, p_{njt} is scaled by the participant's personal (not household) annual income, r_n:

$$v_{njt} = -\alpha\left(\boldsymbol{\omega}\mathbf{x}_{njt} - \frac{p_{njt}}{r_n}\right),$$

where α confounds the marginal utility of cost as a share of income and the scale of the deterministic portion of utility relative to the standardized scale of the random error term,

$\mathbf{x}_{njt}$ is a column vector of the non-cost attributes, $\boldsymbol{\omega}$ is a conformable row vector of unknown marginal WTP parameters to be estimated. Scaling the cost attribute by income allows us to express the cost of each scenario as a share of annual income and estimate the marginal WTP in terms of this cost share. Since participants with lower incomes may be more concerned about costs than those with higher incomes (Train, 2009), the income share allows us to directly consider income in the estimation of the WTP-space utility functions without estimating additional parameters (e.g., see Danley et al., 2021; Giergiczny et al., 2012; Kassahun et al., 2021; Ben-Akiva et al., 1985). Moreover, since income tax is charged at graduated rates, as a percent of income, expressing marginal WTP as a share of income is arguably more useful for policymakers as it may help the calibration of a potential carbon tax. We emphasize that specifying the model in this way inherently embeds a welfare economics interpretation, allowing the parameters of interest to be directly interpreted as the percentage of income respondents are willing to pay.

Under the conditional logit model assumption that ε_{njt} is a deviate from an identically and independently extreme value distribution with constant variance $\pi^2/6$, the probability of the sequence of choices made by participant n is:

$$\Pr(\mathbf{y}_n|\mathbf{X}_n, p_n, r_n, \alpha, \boldsymbol{\omega}) = \prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp(v_{njt})}{\sum_{j=1}^{J}\exp(v_{njt})}\right)^{y_{njt}},$$

where y_{njt} is an indicator variable equal to 1 if participant n choose alternative j in choice situation t, and equals zero otherwise, and y_n is the vector of indicators for the sequence of T_n choices, $\mathbf{y}_n = [y_{nj1}, y_{nj2}, \dots, y_{njT_n}]$. Then the log-likelihood, $\mathcal{L}$, is simply:

$$\mathcal{L} = \sum_{n=1}^{N} \ln \Pr(\mathbf{y}_{\boldsymbol{n}}|\mathbf{X}_n, p_n, r_n, \alpha, \boldsymbol{\omega}).$$

The conditional logit model can accommodate preferences that vary systematically in the sample in relation to observable characteristics. Since the specification of the absolute levels of utility is irrelevant (i.e., only their differences matter), they can only enter the model if they are specified in a way that creates differences in utility over alternatives (Train, 2009). This can be achieved by interacting participants' characteristics with the attributes and/or alternative-specific constants, which provide the mean ceteris paribus effects of the characteristics on utility. However, as the number of participants' characteristics increases, the number of potential parameters to be estimated rapidly increases. Moreover, there is typically little a priori information on which characteristics ought to be included and which interactions are important. Moreover, the ceteris paribus effects might be very different for participants with different characteristics. Therefore, while the interaction might retrieve the ceteris paribus effects close to the average effect, they deliver only highly aggregated information and may not provide any indication about the distribution of these effects in the population. Detecting preference heterogeneity patterns that may be masked by aggregate effects would often be highly relevant for policy analysis, such as exploring preferences across age and income. For these reasons, we move to a non-parametric local conditional logit econometric framework to analyze heterogeneity related to observed participant characteristics for its flexibility to accommodate the underlying (complex non-linear) relationship between utility and participant characteristics. As will be seen, the local conditional logit is both intuitively and mathematically simple, and it avoids the need to make a priori assumptions on which interactions are important and their (non-linear) relationship with the attributes.

2.2 Local model

If we have many observations of $\mathbf{y}_n$ for a combination of Q socio-demographic or personal characteristics denoted by $\mathbf{z}_n$, which is a vector of length Q, it would be possible to estimate α and $\boldsymbol{\omega}$ for this subset of participants and each unique combination of characteristics. For sample sizes typically found in stated choice experiments in environmental economics (approximately 300–1,000), estimating separate models for every unique combination of covariates is feasible only when dealing with a small number of discretely distributed covariates with limited values. However, when multiple covariates are involved—especially if any are continuously distributed—there are likely too few participants with identical characteristics to support such an approach. Nevertheless, it is possible to apply a kernel smoothing method to fit each observation with a conditional logit model using a sample of data points close to the point of interest (i.e., the local sample) in such a way that more emphasis is placed on those observations closest to $\mathbf{z}_n$. Specifically, the local log-likelihood for a reference participant $\overline{n}$, with characteristics $\mathbf{z}_{\overline{n}}$, is expressed as follows:

$$\mathcal{L}_{\overline{n}} = \sum_{n=1}^{N} K_n \ln \Pr(\mathbf{y}_n | \mathbf{X}_n, p_n, r_n, \alpha_{\overline{n}}, \boldsymbol{\omega}_{\overline{n}}),$$

where K_n is the kernel weight assigned to participant n in the dataset and $\alpha_{\overline{n}}$ and $\omega_{\overline{n}}$ are the parameter estimates (i.e., for reference participant $\overline{n}$). Conditional on the local point, the kernel weights reflect the multidimensional 'distance' (i.e., degree of similarity) between the local point and the other points in the dataset. When differences in the characteristics between the reference participant $\overline{n}$ and another participant n become smaller, individual n has a higher kernel weight in the local likelihood estimation of $\overline{n}$ (and vice versa). Therefore, the kernel weights account for the fact that more similar participants in observable characteristics have more similar preferences. The estimation procedure retrieves the local estimates of $\overline{n}$ that maximize this local log-likelihood function. Aggregating the local estimates from all local models produces a smooth, globally non-parametric coefficient function.

Formally, the kernel weight K_n is governed by a set of kernel density functions and smoothing parameters (i.e., bandwidths). The kernel function determines the weight assigned to each data point within the local sample, whereas the bandwidths determine the size of the local sample. With Q individual characteristics, and denoting their corresponding bandwidth parameter by λ_q with the constraint $0 \leq \lambda_q \leq 1$, the kernel weight K_n for participant n can be assumed to be the product of the Q one-dimensional kernel weights, as follows:

$$K_n = \prod_{q=1}^{Q} \lambda_q^{|z_{\overline{n}q} - z_{nq}|},$$

where $z_{\overline{n}q}$ denotes the value of the q^{th} characteristic for reference participant $\overline{n}$, and z_{nq} is the corresponding value for participant n.[2] Individuals with exactly the same characteristics have the same weights in the likelihood function and, therefore, the estimated semi-parametric distribution of preferences is the same for these individuals. The use of this weight implies the clustering of similar values because participants with similar characteristics to $z_{\overline{n}q}$ have a larger bearing on the local model's log-likelihood compared to participants who are multidimensionally distant. Indeed, when participants share the same characteristics with the reference participant $\overline{n}$, $z_{\overline{n}q} - z_{nq} = 0 \forall q$, the resulting kernel weight is equal to one. However, with $0 < \lambda_q < 1 \ \forall q$ as the distance between $z_{\overline{n}q}$ and z_{nq} increases, $K_n \rightarrow 0$, meaning that participant n has less influence on the weighted log-likelihood function. For this analysis, we set $\lambda_q = 0.971$ for all Q, selected using a leave-one-out cross-validation procedure (Sopitpongstorn et al., 2021). Further details are provided in the Appendix.

3 Data

We use data from a study of the Norwegian Climate Forest Programme (CFP) where

[2] For our analysis we only use an individual characteristics, namely age. The kernel function outlined in Equation 6 with geometrically declining weights is commonly used for such variables (see Racine and Li (2004) and Frölich (2006) for a discussion.

the Norwegian government has been considering implementing a national policy of subsidizing and supporting private forest owners in planting forests to improve carbon sequestration on formerly grazed, semi-natural pastures. These semi-natural pastures are presently gradually becoming revegetated by natural forests. In recent decades, 8,500 km^2 of semi-natural pastures (hereafter pastures) have been abandoned, of which 1,350 km^2 have quite recently been abandoned and have not yet become forested. These pastures are now undergoing natural reforestation with mixed forests but could instead be planted with forests (spruce plantations) as a more potent climate sequestration measure. However, the abandoned pastures could also be restored as semi-natural pastures, a land use that potentially could be beneficial for many red-listed species. The planting of climate forests is debated since such land use may reduce biodiversity (Norwegian Environment Agency, 2013; Henriksen and Hilmo, 2015a,b), and may be seen as an impairment of landscape aesthetics (Grimsrud et al., 2020; Liu et al., 2023).

This study uses an online stated choice experiment to measure the welfare effects of land use options for abandoned semi-natural pastures across Norway. The valuation study aimed to investigate the trade-offs between climate, biodiversity and landscape aesthetic effects of the different land use options. The questionnaire first asked warm-up questions about people's preferences for environmental policy objectives. The survey then explained the main topic of the study and the land use challenges related to formerly agricultural or extensively grazed land that is now becoming revegetated with natural forests. The respondents were asked about their preferred option for managing abandoned farmland. Three possibilities for these lands were presented: restore to pasture, remove current vegetation and utilize the land for climate forests (monoculture, Norway spruce) for a period of 60 years, or do nothing and let the land return to natural mixed forests (status quo). Of the three options, only the status quo does not incur an additional cost. The three land use options affect carbon uptake and storage in the vegetation, the level of biodiversity the land can support and landscape aesthetics. The geographical focus of the survey was relevant agricultural areas across Norway.

The attributes of the stated choice experiment were chosen based on input from a focus group and results from a Q-study, which combined qualitative and quantitative data on various stakeholders' opinions and preferences from in-depth interviews supplemented by a population survey (Grimsrud et al., 2020). The first version of the stated choice experiment was tested in an extensive pilot survey and subsequently updated and improved. The pilot data has been analyzed elsewhere (Sandorf et al., 2022; Iversen et al., 2021). Through piloting and careful attribute selection, these steps helped enhance the validity and credibility of the stated choice experiment, although we recognise the potential for hypothetical bias (present in all such studies) necessarily remains. Consequentiality of the survey was emphasised in that respondents were told that the survey was implemented by Statistics Norway (the official statistics and data compiler in Norway), that the government currently considers different land use plans for pastures and that: "..responses from the survey will be part of the decision basis for the use of such areas in the future. It is therefore important that you take the time and answer honestly."

One attribute, land cover, characterised the percentage of land set aside for three options: Planted climate forest, restored as pasture, and reforested naturally. The levels of this attribute were based on findings in the official CFP report and expert knowledge of carbon sequestration and biodiversity (Norwegian Environment Agency, 2013; Henriksen and Hilmo, 2015a,b). This report identifies the total potential land area that could be planted with spruce (Norwegian Environment Agency, 2013). We set the maximum amount of planted spruce or pasture to 50 percent of the total potential land area. In addition, this land use had levels of 25 percent and 0 percent. The amount of the landscape left to reforest naturally was derived as the residual area when the other land uses varied freely.

The motivation for the CFP is, as mentioned, to increase carbon sequestration and storage in the vegetation. The attribute levels of carbon sequestration and storage in the vegetation were calculated for planted spruce and reforestation based on estimates in the CFP report. For pasture, carbon sequestration and storage in vegetation was assumed to be one-third of the carbon sequestered and stored by planted spruce (Norwegian Environment Agency, 2013). The stated choice experiment included information on the potential carbon sequestration and storage in the vegetation for a particular mix of the three land cover options. Note that there also is carbon storage in the soil, but this was not discussed in the information provided to survey respondents because current measurements are uncertain, lacking or vary significantly between locations. Further, we did not mention any potential for leakage nationally or internationally, as the areas and proposed activities are relatively small and likely to have marginal effects outside the confounds of the CFP program (e.g. Schulte et al., 2025).

An attribute described the state of red-listed species in Norway. An estimate of the number of species under threat of extinction in Norway due to the abandonment of pastureland is 685, according to the official red list report of Norway (Henriksen and Hilmo, 2015a). Under no management of the abandoned semi-natural pastureland, it is estimated that 90 percent of the 685 species will disappear from Norway. The two other biodiversity levels are that all 685 species continue to be threatened by extinction, but no species disappear from Norway, and 50 percent of the 685 species will be protected. The impacts on species and extinction levels were based on extensive expert input from leading Norwegian biologists.

A cost attribute, described as the level of extra personal income tax, was included. It was stated that the tax revenue would be earmarked solely for the management of abandoned pastures. The cost levels were based on feedback from the focus group and one-to-one interviews with test survey participants. All the attributes were thoroughly explained to participants prior to the stated choice experiment, using photographs that were manipulated to show how semi-natural pastures in different regions of Norway would change if they were planted with climate forests or naturally reforested. An overview of the attributes and their levels are presented in Table 1.

Table 1: Attributes and levels

Attribute	Attribute label	Levels	Level label
Annual cost per person (per 1,000 NOK)	Cost	0.00, 0.24, 0.48, 0.96, 1.44, 1.92, 3.84	
Land cover (percent/100 land cover)	Land	Area covered by forest: 0.00, 0.25	Forest
		Area covered by grazing: 0.00, 0.25, 0.50, 0.75	Grazing
		Area overgrown (baseline)	
Carbon sequestration (per 1,000,000 tonne)	Carbon	0.40, 0.70, 1.50	
Species protection	Species	685 species are still threatened by extinction	AllSpecies
		50 percent of the 685 species will be protected	HalfSpecies
		90 percent of the 685 species will disappear (baseline)	

Each respondent received six choice tasks and was asked to choose between two policy options (Management Options A and B) in addition to the status quo (No management). We show a sample choice task in Figure 1. The order of the choice sets was randomized between individuals. The choice sets were followed by standard follow-up questions regarding which attribute (if any) they thought was the most important and whether it was difficult to answer. The survey then had a series of questions about nature-based recreation, and whether there are areas within Norway where people prefer no climate forest planting. The questionnaire concluded with socioeconomic background questions. The experimental design was generated using NGENE (ChoiceMetrics, 2012). We chose to use a fractional factorial design with 18 choice tasks in three blocks. The design was constrained to prevent the lowest level of red-listed species from occurring together with the highest levels of the area allocated to spruce planting.

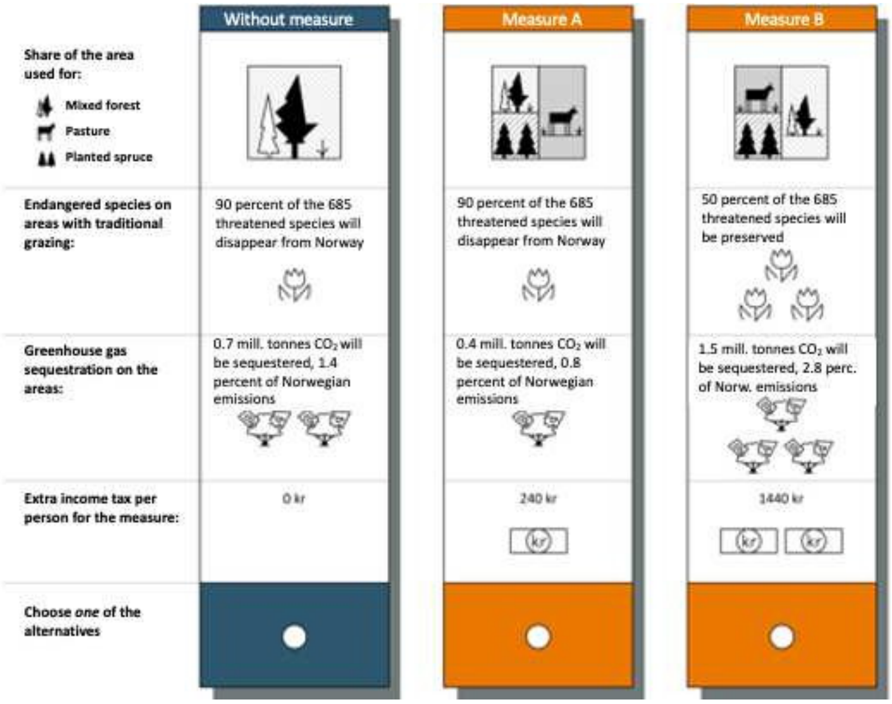
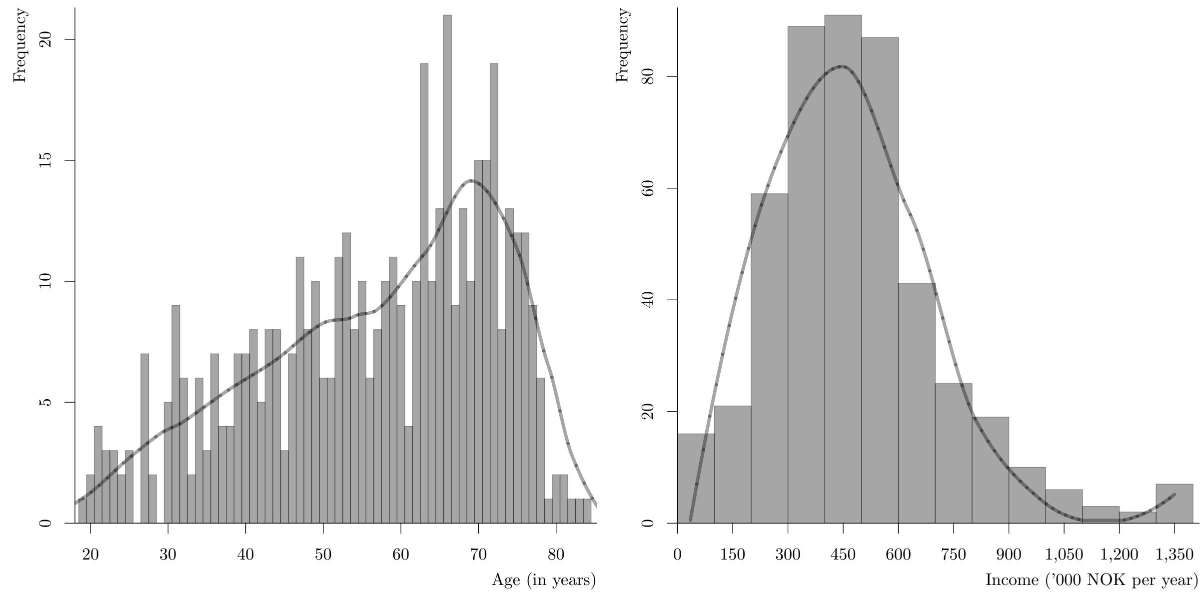


Figure 1: A sample choice task (translated to English)

The survey was tested in focus group discussions and adjusted before a series of in-depth one-to-one interviews. Thereafter, the survey was piloted in an online survey. The final data were gathered using an online stated choice experiment between December 2018 and February 2019, where participants were sampled from a pre-recruited high-quality internet panel judged to be representative of the Norwegian adult population. The survey was implemented by the reputable company NORSTAT. The overall response rate for the survey was over 20 percent, whereas non-responses included participants who did not complete all survey questions. This analysis uses a sample of 478 participants[3]. Each participant completed a sequence of choice tasks, resulting in 2,868 choice observations for use in model estimation. In line with the demographic characteristics of the Norwegian population, our sample consists of approximately equal numbers of male and female participants. The breakdown by age and income is presented in Figures 2a and 2b, respectively. Participants reported their actual age and their annual income as belonging to one of fourteen intervals, and we used the midpoint of each interval as a proxy.

[3] Data from a contingent valuation part of the survey were analysed for another purpose in Iversen et al. (2022).



(a) Age distribution (b) Income distribution

Figure 2: Sample characteristics

4 Results

4.1 Global model results

The results from the global conditional logit model are reported in Table 2. This model serves as a baseline model. By specifying all models in WTP-space, the welfare-economic interpretation is embedded directly in the parameterisation. To make this connection explicit, we reiterate that all ω parameters can be interpreted as marginal WTP, expressed as a percentage of income.[4]

As expected, the marginal WTP as a share of income for each attribute is positive and significant. The estimates can be interpreted directly as the percentage share of their income that people are willing to pay. For example, p eople are willing to pay up to 3 percent of their annual salary to have an area used for grazing rather than becoming overgrown. The marginal WTP for planting climate

[4] For reference, with a median annual income of 450,000 NOK, 1% of income corresponds to 4,500 NOK. Using an approximate exchange rate at the time of the survey (1 EUR ≈ 9.7–9.9 NOK), this translates into a marginal WTP of roughly €460.

forests is just less than 2.5 percent, slightly less than the respective value for protecting species.

Table 2: Global conditional logit model results

	Coefficient	Confidence interval
α	-0.437*** (0.095)	
ω_{Forest}	2.413*** (0.592)	[1.253, 3.573]
ω_{Grazing}	3.057*** (0.752)	[1.583, 4.531]
ω_{Carbon}	0.751*** (0.208)	[0.342, 1.160]
$\omega_{\text{AllSpecies}}$	1.913*** (0.401)	[1.127, 2.698]
$\omega_{\text{HalfSpecies}}$	2.672*** (0.560)	[1.575, 3.770]
$\omega_{\text{Alternative1}}$	0.761*** (0.291)	
$\omega_{\text{Alternative2}}$	0.244** (0.108)	
Log-likelihood	-2,720.659	

Notes: 2,868 choice occasions over 478 respondents. Standard errors in parenthesis. All estimated standard error are robust and clustered at the individual level. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% level.

Key to our research question and focus of this paper is the observed heterogeneity across the age distribution. To facilitate comparison with the local models, which are estimated for every age, we estimate a global model where we interact each parameter with a proportionally rescaled age variable A_n (such that $A_n = 0$ for 18-year-olds and $A_n = 1$ for 80-year-olds). This is the standard approach when considering observed heterogeneity in the MNL model. To capture non-linear effects of age in this framework and enable a fairer comparison with local models (which can naturally capture both linear and non-linear patterns), we use a quadratic specification for age. Specifically, for the parameters specified in WTP-space, the taste parameter ω, is defined as:

$$\omega_n = \omega_0 + \omega_1 A_n + \omega_2 A_n^2,$$

while the parameter that jointly captures cost and scale, α_n, is defined as:

$$\alpha_n = \alpha_0 + \alpha_1 A_n + \alpha_2 A_n^2.$$

Thus, to be absolutely clear about the specification used, the systematic (observed) component of utility for individual n, alternative j, in choice task t is:

$$v_{njt} = -(\alpha_0 + \alpha_1 A_n + \alpha_2 A_n^2)\left[\sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} (\omega_{0k} + \omega_{1k} A_n + \omega_{2k} A_n^2)\, x_{njtk} - \frac{p_{njt}}{r_n}\right].$$

While we chose a quadratic specification here, it should be noted that to fully capture the correct non-linear pattern of the interaction, other competing specifications should be tested. We also note that since the WTP-space specification is already non-linear-in-the-parameters, which can make convergence difficult; adding a quadratic interaction to the mix can compound this issue further. But doing so allows us to capture a non-linear relationship between age and all variables that enter the WTP-space utility expression without complicating estimation too much. The approach provides flexibility in modeling how the effect of age changes across its range. The main argument for allowing interactions to have a non-linear impact is to capture more complex and realistic patterns, ensuring a more meaningful comparison against results from the local models. For example, our main point of departure in this paper is that marginal WTP differs across the age distribution, and because we are working with income shares, it is reasonable to assume that the age effect is not necessarily constant. For example, the effect of age may increase up to a point before decreasing. By including both age and age squared, the model can capture this non-linear, possibly quadratic, relationship more flexibly. However, we acknowledge that because age and age squared enter both the WTP-space taste parameters (i.e., the preference-space parameters divided by the cost parameter) and the cost-scale parameter in the WTP-space model, their net effect is not predetermined. In particular, the influence of age may partially cancel out (since it appears in both the numerator and the denominator of the implied preference-space coefficients) but it may also amplify the overall age effect, depending on the relative magnitudes and signs of the interacting terms. We report the results of this model in Table 3.

Table 3: Global conditional logit model (with age interactions) results

	Intercept		A_n		A_n^2	
α	-0.089	(0.060)	-0.510	(0.362)	-0.249	(0.429)
ω_{Forest}	-3.238*	(1.869)	22.252***	(5.386)	-19.121***	(4.057)
ω_{Grazing}	7.174**	(3.189)	-6.920**	(2.918)	0.584	(1.423)
ω_{Carbon}	1.329	(0.962)	-0.565	(2.339)	-0.578	(1.498)
$\omega_{\text{AllSpecies}}$	4.017***	(1.237)	-2.523	(3.240)	-1.085	(2.466)
$\omega_{\text{HalfSpecies}}$	7.019***	(1.218)	-9.119***	(3.150)	3.230	(2.389)
$\omega_{\text{Alternative1}}$	0.276	(1.338)	6.895***	(1.382)	-8.354***	(1.450)
$\omega_{\text{Alternative2}}$	0.622	(0.760)	-1.957	(1.833)	1.774	(1.206)
Log-likelihood			-2,694.066			

Notes: 2,868 choice occasions over 478 respondents. Standard errors in parenthesis. All estimated standard error are robust and clustered at the individual level. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% level.

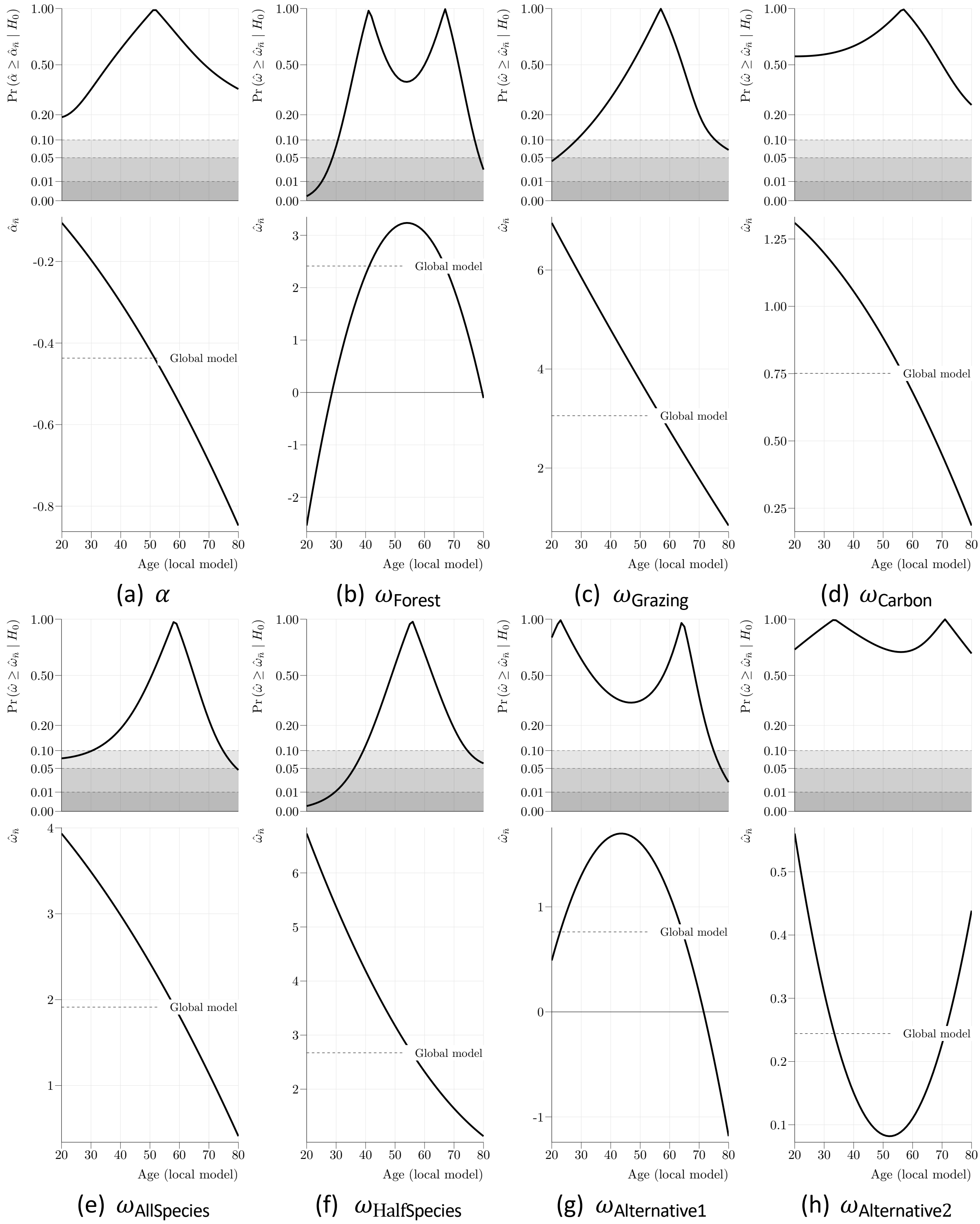
A potential downside of using a quadratic specification is that it complicates the interpretation of the results. We note that there is a switch in the sign between the linear and quadratic terms, which indicates a turning point. When the linear term is positive and the squared term is negative, it suggests an initial increase followed by a decrease in the effect of age, i.e., a diminishing marginal impact. This pattern is observed for attributes related to the forest and the status quo (SQ) alternative-specific constant. Conversely, when the linear term is negative and the squared term is positive, it implies the opposite trend. This is seen for the 50% of species protected level and the grazing attribute, but the squared interaction terms are insignificant. When both terms are negative, it suggests that the negative effect is compounded by age. This is observed for cost, carbon sequestration, and all species are protected, but the interactions are insignificant. Overall, age appears to have a significant and non-linear relationship for forest and the SQ.

To aid with interpretation, in Figure 3, we show how the resulting derived parameter for each age between 20 and 80 varies. In the top panel of each subfigure, we show the *p*-value for a two-tailed test. Where the line "dips" into the shaded areas indicates where the model estimates are different from the baseline model. The deeper the dip, the higher the level of statistical significance. In the bottom panel of each subfigure, we show how the calculated parameter varies across the age distribution. We see that, compared to participants aged in the middle of the range, the very youngest and very oldest participants are found to be willing to pay a significantly lower share of their income towards climate forest. The turning point can be found by setting the derivative of ω with respect to age to zero and solving for age. The turning point for the share of income participants are willing to pay for the forest attribute is 54.1 years (95% CI, 49.0, 57.4). Up to this age, there is an increase in the share of income participants are willing to pay, after which it decreases.

Turning our attention to marginal WTP for grazing, we see a downward trend with age in the share of income people are willing to pay. Compared to the global baseline model, the very youngest are willing to pay a significantly higher share of income for grazing, with older people willing to pay significantly less. We observe the same downward trend for carbon sequestration, although it's worth noting that the differences in marginal WTP as a share of income are not statistically significant. Hence, the relationship between these attributes/levels and age is not supported in the model. To test if age indeed does not explain any of the difference here, it is necessary to test whether the retrieved values of the share of income that the youngest participants are different compared to those retrieved for the oldest participants are willing to pay. We can confirm that the difference in the value predicted for participants aged 20 years versus 80 years is not statistically different. Thus, we can conclude that, based on this model, age plays no role in the share of income participants are willing to direct towards carbon.

A similar pattern to grazing is observed for both species levels: we observe that very young and very old respondents have a significantly different marginal WTP compared to those in the middle of the age distribution and compared to the global model. Looking at the SQ, perhaps somewhat surprising, is that the oldest participants are less likely to choose the SQ, meaning they do choose one of the policy options. Whether this concerns future generations or a sense of nostalgia for pastures long gone, we cannot say[5]. What we can say is that the turning point for the tendency to choose the SQ alternative, all else being equal, is 43.6 years old (95% CI, 32.7, 60.6). At this age, participants are most likely to choose the SQ, with the propensity decreasing for respondents both older and younger. The alternative-specific constant for alternative 2 is insignificant across the distribution, meaning that the mean of the unobserved factors relating to this alternative (with respect to alternative 3, i.e., the rightmost alternative) is independent of age.

[5] Liu et al. (2023) finds that Norwegians born before 1970 showed some preference for maintaining agricultural landscapes.



(a) α (b) ω_{Forest} (c) ω_{Grazing} (d) ω_{Carbon}

(e) $\omega_{\text{AllSpecies}}$ (f) $\omega_{\text{HalfSpecies}}$ (g) $\omega_{\text{Alternative1}}$ (h) $\omega_{\text{Alternative2}}$

Figure 3: Global conditional logit model (with age interactions) results

The "cost"- parameter, α, becomes increasingly negative as age increases, but interpreting this is complicated due to its confounding with the scale parameter. Nonetheless, none of the predicted values of α for a given age is statistically different from those obtained in the baseline conditional logit model, suggesting that age does not significantly influence the value of α. That said, as previously mentioned, this does not necessarily imply that the values of α for the youngest and oldest participants are not significantly different; they are. Rather, the statistical significance test shown in Figure 3 is conducted against the global conditional logit model. These results combined suggest that age does indeed explain all attribute levels, with the sole exception of carbon, and that it also plays a part in the alternative-specific constants.

Taken together, the global model results show that preferences, and particularly marginal WTP, vary systematically with age. We observe a clear downward trend in the income share respondents are willing to pay as age increases, with the exception of a notable rise around age 50-60 for the forest attribute level. This highlights that support for climate-related and environmental improvements is not uniform across age groups. Such heterogeneity carries important policy implications: ignoring age-related differences in WTP risks misjudging public support, leading to policies that may be less effective, less equitable, or more difficult to implement. Recognising these gradients can help policymakers design interventions that are more socially inclusive and more likely to gain broad-based acceptance.

4.2 Local model results

While the global model reported above directly considers income in estimating marginal WTP, it does not consider other aspects important to assessing inter-generational impacts. We considered age in a modified model where we allowed age to enter non-linearly. While including age in the global model can capture the general relationship that age has on marginal WTP, it may not be as effective as using a semi-parametric approach. In particular, the functional form is predetermined and assumes a specific shape for its relationship. On the other hand, the semi-parametric offers more flexibility, allowing the data to determine the functional form of the relationship. For this reason, we consider these results next.

We estimate a model that explicitly considers that people of a similar age have similar preferences. The local logit model is estimated for all points over the age range (20-80 years), leading to 61 local models. In Figure 4, we show the effective sample size for each local model. Note that the effective sample size differs between local models and that the shape of the sample size distribution mimics that of age. This occurs because there are relatively more respondents aged 50–70 compared to the extremes. Additionally, local models centred in the middle of the age distribution draw data from both sides, while those at the extremes rely only on one side.

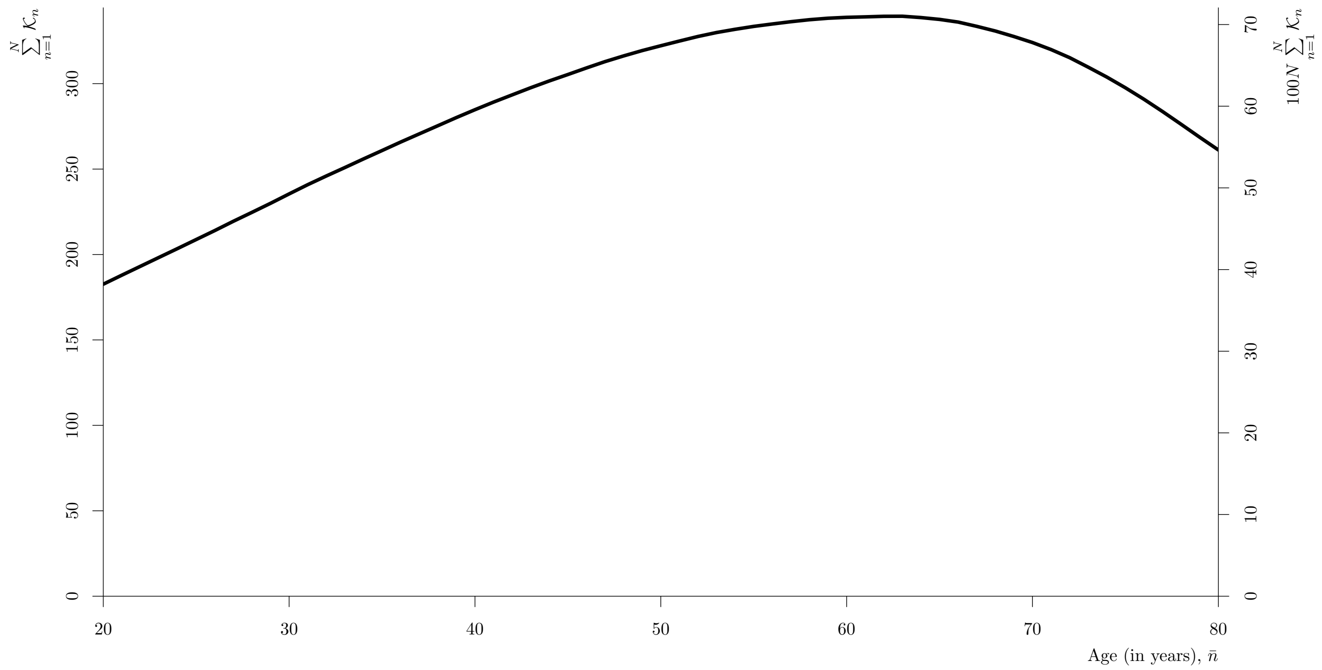


Figure 4: Effective sample size for local models

In the bottom panel of Figure 5, we present the smoothed parameter function over the local model for each parameter. In the top panel, we show the *p*-value for a two-tailed test denoted using $\Pr(|\widehat{\omega}| \geq |\widehat{\omega_{\bar{n}}}||H_0)$, i.e. $H_0\colon \widehat{\omega} = \widehat{\omega_{\bar{n}}}$ versus $H_0\colon \widehat{\omega} \neq \widehat{\omega_{\bar{n}}}$. The *p*-values are calculated using an independent samples t-test, $2\Phi(|\widehat{\omega} - \widehat{\omega_{\bar{n}}}|/\sqrt{s_{\widehat{\omega}}^2 + s_{\widehat{\omega_{\bar{n}}}}^2}$, where s is the standard error (with all estimated standard errors being robust and clustered at the individual level). Where the line "dips" into the shaded areas indicates that the estimate from the local model is significantly different from the global model. The deeper the dip, the higher the level of statistical significance.

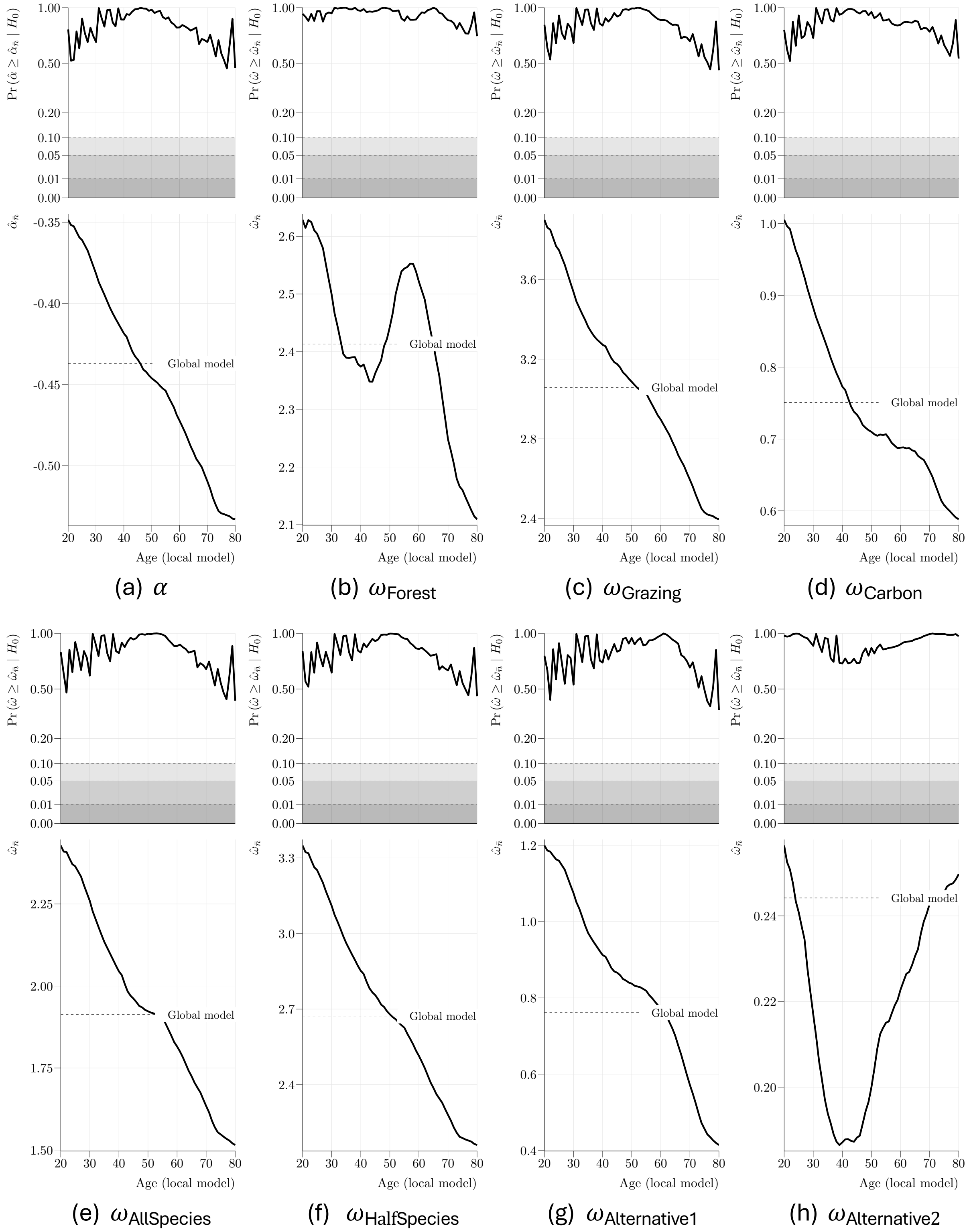


Figure 5: Local conditional logit model results

It is immediately clear that there is (observed) heterogeneity in the parameter estimates. When we consider the cost parameter (Figure 5a), we see that, as expected, the estimate is negative and becomes increasingly negative with age. However, given the confounding with the scale of the model, interpretation is not clear-cut. We also note that across the age distribution, it is not significantly different from the global model. We also estimate the alternative-specific constants in WTP-space as a share of income with respect to Management Option B (the rightmost alternative). For Alternative 1 (the No management or SQ option), there is a clear signal that the willingness to stick with the SQ differs across the age distribution (Figure 5g). Ceteris paribus, the propensity to choose this alternative drops with age, and at the upper end of the age distribution, the difference is statistically significant. The effect is quite different for alternative 2 (Figure 5h), where it drops but then rises from around 40 years of age. However, we do need to be mindful of interpreting the marginal WTP for the alternative-specific constants, as they can be influenced both by the label attached to the SQ and display order.

The differences across the age distribution also carry through to how much people are willing to pay for climate change mitigation. Estimates show that marginal WTP as a fraction of their income is high for the youngest participants but drops quickly with age. Across all attributes, except for climate forest (Figure 4b), we see a consistent pattern across the age distribution. In general, the marginal WTP as a share of income decrease with age. This means that younger people are willing to pay a higher share of their income towards climate policies that include these attributes than older people. Note that these differences are not statistically significant when compared with the average sample estimate from the global model. However, when comparing the estimates for the very youngest respondents with those for the very oldest, the differences become statistically significant. The distribution of the smoothed parameters for the forest attribute appears to be bi-modal, with peaks between 20 and 30 years and around 60 years. While pure speculation, it could speak to relatively higher disposable income levels for these age groups.

Notwithstanding the lack of significance against the global model, the strong, clear, and consistent pattern supports the current modelling approach. It indicates that there might be an effect at play that is not detectable with the relatively small sample used in the current paper. Comparing the global model with age interactions and the local models, we argue that the global conditional logit model based on a quadratic specification for age is too simplistic. The functional form is predetermined and assumes a specific shape. As is evident, it was not flexible enough to capture some nuanced patterns between age and marginal WTP. This could, of course, be captured by allowing for higher-order polynomials beyond quadratic and could provide a more detailed understanding of the relationship between variables in certain cases, allowing for the capture of more nuanced results. However, such approaches are generally not recommended for several reasons. Firstly, higher-order polynomials can introduce complexity and overfitting, leading to models that perform poorly on new data. Additionally, as the polynomial degree increases, the interpretation of coefficients becomes increasingly challenging and may lead to spurious relationships. Furthermore, higher-order polynomials can amplify noise in the data, making the model less robust and reliable.

The semi-parametric kernel models, i.e., the local models, avoid this. This approach enables the model to adapt to the data and capture nonlinear relationships in a more flexible and data-driven manner. Moreover, for several attributes, the global conditional logit model based on a quadratic specification for age produces marginal WTP values that are more extreme and outside a reasonably plausible range. In particular, it suggests that participants aged under 30 years have a negative marginal WTP for forests, which seems to make little sense. Overall, the range in marginal WTP estimates is narrower under the local models, which is expected since the model takes account of the whole dataset.

All of this said, we recognize that some of the merits of the local conditional logit models with kernel smoothing over the global conditional logit model based on a quadratic specification for age are largely driven by our choice of kernel weight. Had we used a smaller bandwidth parameter, the results would exhibit greater variability, with potentially more extreme values and a wider range (perhaps even more so compared to the results obtained from the global conditional logit model based on a quadratic specification for age).

Taking the local model results at face value, the findings reinforce the policy-relevant conclusion that WTP, as a share of income, does vary systematically with age. This implies that increases in fiscal instruments such as income tax or targeted levies to fund climate-related actions are, on average, likely to encounter less opposition from younger respondents. Moreover, for revenue-raising measures linked specifically to the forest attribute, resistance also appears lower among those around age 60. Although we do not elaborate on the interpretation of the alternative-specific constants, their apparent relationship with age carries additional policy resonance. In particular, the results suggest that overall support for any policy that departs from the status quo tends to increase with age.

5 Conclusion

Compared to other environmental policies, climate change mitigation policies can have pronounced distributional effects. Therefore, evaluating the costs and benefits of climate change mitigation requires an understanding of how preferences and priorities differ across people. In this paper, we explore how these differences can be accommodated in the analysis of data from stated preference choice experiments. Specifically, we investigate how survey participants' marginal willingness-to-pay (WTP) for a carbon sequestration program differs across both the age and income distributions. This is motivated by the fact that young people will likely experience both the costs and benefits of the program within their lifetimes, whereas older people are primarily affected by its costs. Similarly, the effects of climate change may disproportionately impact poor people. To achieve this, we use a set of local conditional logit models in WTP-space where cost is scaled by personal income with kernel smoothing to accommodate observed preference heterogeneity within a semi-parametric econometric framework.

The results show that WTP for the carbon sequestration program is relatively lower for older respondents compared to younger respondents. This is a result that resonates with political movements in many countries where young people are advocating for more stringent and effective climate policies at high costs, for example, the movement led by Greta Thunberg: "School strike for the Climate". Studies that focus on other environmental goods, for example biodiversity, tend to find that overall marginal WTP increases with income but that the income elasticity is less than one (Jacobsen and Hanley, 2009) or that marginal WTP for public goods, in general, is lower if income inequality is higher in cases where the environmental good can be substituted for a manufactured good (Baumgärtner et al., 2017).

Several implications can be drawn from the results. From the policy perspective, the results indicate that the estimated benefits of climate change mitigation are considerable. Results from our model prove to be more informative than the single values of central tendency, which are normally reported in discrete-choice experiment studies. Our findings confirm that there is (observed) heterogeneity in how much people are willing to pay for climate change mitigation and that our suggested approach seems to work well at uncovering this heterogeneity. We find unequivocal differences across the age distribution in the propensity to choose some alternatives and the marginal WTP estimates. In particular, while younger people are more likely to choose the status quo option, they are estimated as having the highest marginal WTP for attributes of the climate change mitigation policies. Incorporating distributional considerations into climate change mitigation planning is essential for designing efficient and welfare-enhancing policies that reflect heterogeneity in preferences across age and income groups. Because income tax is levied at graduated rates, expressing marginal WTP as a share of income is particularly informative for policymakers, as it facilitates calibration of potential carbon taxes or subsidies for carbon sequestration programmes. The modelling framework developed here enables the estimation of environmental values at a more disaggregated level, and examining these distributional patterns in finer detail offers policymakers additional insight for designing more precisely targeted interventions.

Moreover, public funds can be allocated more efficiently when environmental education and behavioural initiatives are tailored to specific demographic groups. Such approaches are not without precedent: many European countries provide heavily discounted or free public-transport passes for young people, often justified on climate grounds by encouraging long-term low-carbon travel habits. Likewise, several countries have introduced compulsory climate-education curricula targeted at younger age cohorts, with the explicit aim of fostering sustained pro-environmental behaviour. These examples illustrate how age-targeted policy design can complement broader climate-mitigation strategies.

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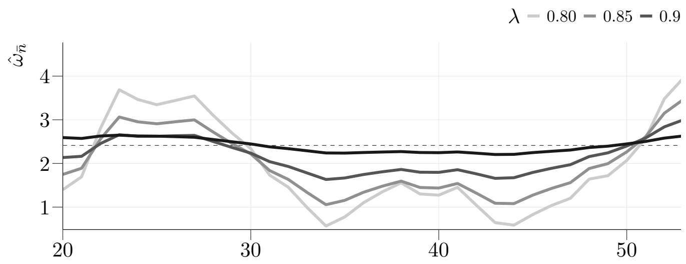
Appendix: Bandwidth selection

The bandwidth controls the complexity of the model, and its choice plays a crucial role in the local models. Instead of using a different bandwidth for each characteristic, it is common practice to assign the same bandwidth for all Q dimensions $\lambda_q = \bar{\lambda}$ (Racine and Li, 2004). Following Frölich (2006), to adjust for different scopes and measurement scales and to improve numerical stability, the distribution for each characteristic can be converted into standard scores to ensure all distributions have the same mean and standard deviation. If $\bar{\lambda}$ is low, then only the participants with very similar characteristics influence the local model. Specifically, with weak smoothing $\bar{\lambda} = 0$, the model is a saturated model, resulting in a separate estimation of a conditional logit model for each unique combination of individual characteristics. Conversely, for strong smoothing, the product of kernel functions would be similar regardless of the local distance between $\bar{n}$ and n. Indeed, with $\bar{\lambda} = 1$ all local models will retrieve the same parameters of the conditional logit model for the whole sample. The optimal bandwidth, therefore, depends not only on the number of participants and their multidimensional distance from each other but also on how well the global conditional logit model explains the true patterns of preference heterogeneity. If the conditional logit model can detect the true patterns of preference heterogeneity, the optimal bandwidth would be $\bar{\lambda} = 1$, corresponding to the global log-likelihood. Otherwise, the bandwidth should tend to zero with increasing sample size. For intermediate cases, we have $0 < \bar{\lambda} < 1$ as the optimal bandwidth.

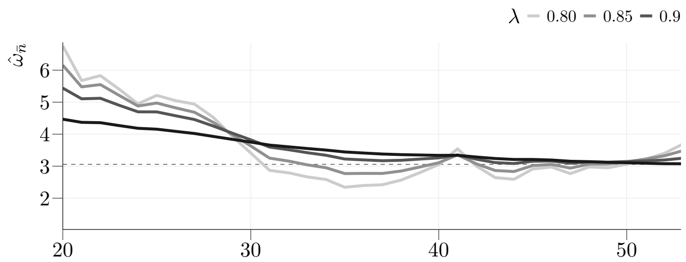
A range of methods exist in the literature for selecting the bandwidth parameter, and no single approach is universally preferred (Dekker et al., 2014). In this paper, we choose a bandwidth that balances the likelihood function with a leave-one-out cross-validation procedure (Sopitpongstorn et al., 2021; Pagan and Ullah, 1999), while also avoiding excessively small local samples in sparsely populated regions of the data; an issue mitigated by selecting a relatively high bandwidth. This process yields an optimal bandwidth of $\lambda = 0.971$, which provides the best overall fit across the set of local age-specific models. We consider this bandwidth level to strike an appropriate balance between mitigating the risk of sparse observations due to gaps in the age distribution and overfitting the model to the global specification. Moreover, smaller bandwidths effectively increase model complexity by raising the number of parameters needed to estimate the relationship, making local models less parsimonious and overly tailored to the data. A larger bandwidth, by contrast, substantially reduces this risk.

Because bandwidth choice can materially influence the results, and inappropriate selection may lead to misleading inferences, we conduct a set of robustness checks. Figure A1 presents the marginal WTP estimates for each attribute by age using alternative bandwidths from 0.80 to 0.95, in increments of 0.05. As expected, the broad pattern is consistent across specifications, though lower bandwidths generate greater fluctuation, while higher bandwidths smooth the estimates and converge toward the global model. Increasing the bandwidth to 1 (not shown) produces identical estimates across ages, equivalent to the global model.

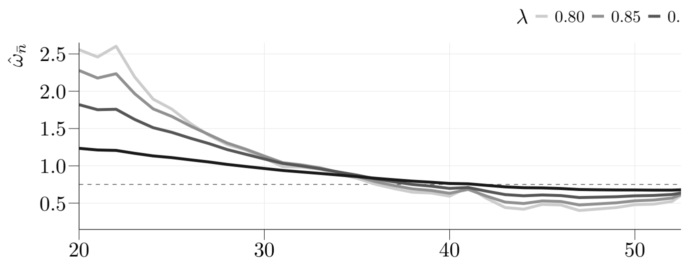
Since our selected bandwidth of 0.971 lies between the highest value shown (0.95) and the global model, the resulting predicted curve falls between these extremes. Its exact profile is presented in Figure 5, and is therefore not repeated here to avoid redundancy and visual clutter.



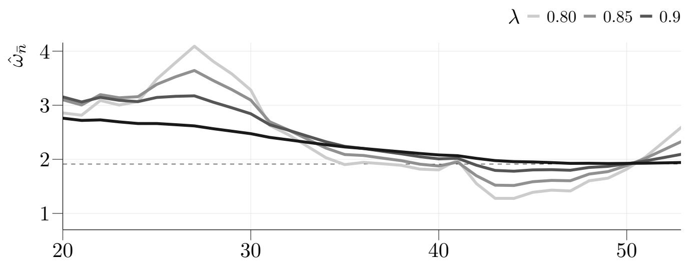
(a) Forest



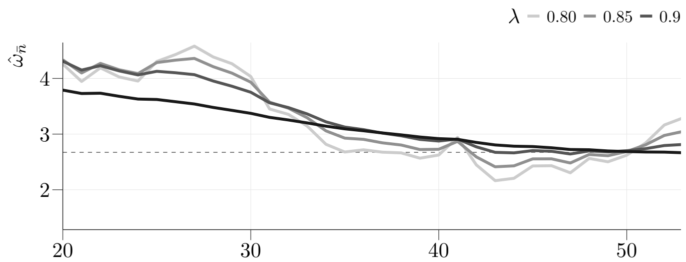
(b) Grazing



(c) Carbon



(d) AllSpecies



(e) HalfSpecies

Figure A1. Distribution comparison under alternative bandwidth choices