"Moor, later?" – Effect of payment schedule timing in choice experiment: application from mire conservation in Finland

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Abstract

We study consumers' time preferences through four payment schedules using a split sample design with choice experiments in the context of mire conservation programs. First, we compare lump-sum and ten-year annual payment schedules finding insensitivity to the length of payment period. Second, we compare ten-year payment periods starting immediately, three and six years later to elicit implicit discount rates between samples. The results may give support to hyperbolic discounting. We also study preference and scale heterogeneity among respondents which we find independent from payment schedules.

1. Introduction

The timing of benefits and costs of action are at the core of cost-benefit analysis. The economic feasibility of a lengthy environmental restoration (conservation) project with immediate (opportunity) costs and slow flow of benefits over time is sensitive to the choice of discount rate. Where the appropriate social discount rate in cost-benefit analysis of intergenerational policy effects is a discussion in itself (Freeman and Groom 2014), the discount rate within the current generation remains an area in need of examples. The public's discount rate for environmental benefit flows has been studied by altering the schedule of providing the good and payments, both separately (Viscusi et al.2008 and Egan et al. 2015, respectively) and jointly (Andersson et al. 2013). These approaches have mostly employed the contingent valuation (CV) method. As Smith (1992) has earlier noted, time horizon issues are not unique to CV studies, but exist also in actual choice situations. More recently, Egan et al. (2015) call for investigation on how consumers consider payments in different settings and time horizons. We employ choice experiments (CE) to study the effect of varying payment schedule under a fixed long term environmental change in a mire conservation/restoration setting.

Egan et al. (2015) argue that lump-sum payments cause underestimated values and requires consumers to estimate the present value by themselves – problematic in valuing environmental goods with constant or slowly changing stream of benefits. Their solution is to preferably offer a perpetual annual payment schedule. When policy measures and the resulting costs are immediate and environmental improvements are spread over a long time horizon, perpetual payment schedule may not be easily defended (e.g. asking for a permanent raise in income tax for a one-time conservation area acquisition program). This case study focuses on ecosystem services provided by mires in southern Finland up until the year 2050. As the conservation of mires produces, on aggregate, a slowly increasing flow of benefits it provides a good case to analyze the effect of payment schedule that does not affect the expected realization of environmental effects of policy.

The typical approach in analyzing the effect of payment schedule to willingness to pay (WTP), or the embedding effect in timing, has been to compare a lump-sum payment with some series of payments (Andersson et al. 2013, Bond et al. 2009; Brouwer et al. 2008; Egan et al. 2015; Kahneman and Knetsch 1992; Kim and Haab 2009; Kovacs and Larson 2008; Stevens et al. 1997; Stumborg et al. 2001). The earlier literature suggests that WTP per payment occasion is quite insensitive to the number of payment occasions, i.e. the *total* WTP increases with the number of payment occasions.

In addition to split sample designs, comparisons of lump-sum payment, annual payments for finite periods and perpetual payments (Egan et al. 2015 ; Kim & Haab 2009), and the effect of payment period length have been studied (Stumborg et al. 2001, Bond et al. 2009). Bond et al. (2009) found no distinguishable difference between payment schedules of one and five years, where difference emerged between payment schedules of five and fifteen years. Some researchers have altered the length of the payment time. For example, Kovacs and Larson (2008) applied monthly payments for 12, 48, 84, 120 month periods, keeping the net present values of bids similar.

Brouwer et al. (2008) allowed respondents to choose the payment period. Their results maintained the finding that annual payments are, on average, significantly higher than lump-sum donations, suggesting a negative implicit discount rate between lump-sum payments and multi-payment schedules. To the best of our knowledge there are no studies altering the timing of equal-length payment schedules with equal bid vectors.

Using CV-survey WTP estimations with different time horizons, previous studies have found implicit discount rates ranging between 20% and 270% (Egan et al. 2015). Temporal effects have been suggested to have either strong or weak insensitivity to payment schedule. Strong insensitivity to payment schedule implies the inability of respondents to differentiate between series of payments and lump-sum payments. Weak insensitivity allows for inequality of individual WTP between two temporally differentiated payment schemes but may indicate abnormally high discount rates (Stevens et al. 1997).

Egan et al. (2015) have suggested several reasons for insensitivity in timing of the payment. First, respondents may have mental accounts for charitable giving and will feel more constrained by a large one-time payment compared to a relatively small annual payment. Second, respondents may simply not think about the future or, third, take the valuation task seriously. Finally, respondents may not be able to discount.

In this study we take two approaches to analyze the effect of payment schedules on implicit discount rates, first, the comparison of lump-sum and annual payments and second, the comparison of different timings of equally long annual payment periods. Including both of these treatments in one study provides opportunities to analyze the relative strength of the time embedding effect in relation to pure understanding of the timing of payment in a more or less distant future period.

Expanding the topic of payment time schedule variation effect to choice experiments from earlier CV approaches provides new opportunities. It is especially interesting to look whether the payment schedules have an effect to preference or scale heterogeneity in choices. Allowing scale heterogeneity choice experiments provide opportunities to analyzing respondent uncertainty thus possibly revealing something about the individual (in)ability to understand the timing of payment as suggested by Bond et al. (2009).

We next describe the case study, data collection and choice experiment and time-frame treatment design in the data and methods section. The econometric models and discount rate calculation are explained in a respectively named section followed by results and end discussion.

2. Case study description

Finland is a country of mires – over a quarter of the nation's land area is categorizable as one of over a hundred different mire biotope types (Metsähallitus, State Forest Enterprise 2016). While mires in natural state provide poor growth conditions for wood biomass, the majority of mires in Finland have been drained for the use of forestry. Mires have also been cleared and drained for peat extraction and, to a smaller degree, agricultural use. Concerns for self-sustainability and political impetus on bioeconomy-based economic growth have increased pressure to increase the use of peat as an energy source. Peat is burned as a primary or secondary fuel in e.g. wood chip reactors to produce both heat and electricity. Maintaining the current peat use in energy production requires tripling the current production area, about 400 km^2, by 2050 to 1 200 km^2.

Ecosystem service provision is in direct conflict with most economic activities on mires. Draining typically deteriorates and mechanical soil preparation related to peat extraction essentially shuts down mires' functioning as a habitat for animal and plant species, and hinder recreational activities (e.g. berry picking and hiking). Peat extraction areas release large amounts of carbon to the atmosphere. After extraction mires restore naturally over decades.

The most recent estimate in 2008 lists roughly 50 % of the mire biotopes of undrained mire areas in Southern Finland as endangered and 40 % as near threatened (Kaakinen et al. 2008). The current conservation area is considered inadequate (Ministry of the Environment 2017) despite mire protection in national and nature parks, old forest protection areas and through the Mire Protection Program (from years 1979 and 1981). Mires on privately owned areas have been protected to some extent on voluntary basis through the METSO-programme (The Forest Biodiversity Programme for Southern Finland). However, especially, the nutrient rich open peatlands (fens) and forested peatlands (swamps and coniferous swamps) are under threat.

In late 2014 the Finnish Ministry of the Environment postponed a prepared update to the Mire Protection Program – the Complementing Mire Protection Program (CMPP) aimed to conserve biodiversity by protecting spatially connected areas with high natural values. The focus of the legislator shifted from government enforced actions to favor voluntary participation by private land owners. The new approach was renamed the Proposal for Complementing Mire Protection. As there is inherent uncertainty in the success of a voluntary program, we study mire protection scenarios better and worse to the goals of the original CMPP.

3. Choice experiment design and data collection

3.1 Design of the choice task

We use the CICES classification (CICES 2016) of ecosystem services to identify the relevant set of ecosystem services provided by additional mire conservation. After the initial identification of significant services, we searched for spatially explicit data to describe their status. Finally, we called a focus group discussion to identify the most important services to be used as attributes in a choice experiment.

The focus group discussion found mire ecosystem services largely related to non-use values. This, in combination with uncertainty of the spatial coverage and subsequent environmental effects with a voluntary protection program, gave reason to use a national population sample. We split the effects from mire protection into five spatially aggregate attributes: climate effects and carbon storage, mire species diversity, water quality, area of mires suitable for berry picking, and change in the level of peat production and the share of domestic fuels in national energy production (Table 1). The final attribute was added to take into account the effect of peat production on local employment and energy self-sufficiency in people's choices.

To determine realistic attribute descriptions and levels we used expert advice and GIS analyses for four scenarios. GIS analysis was used to identify likely peat extraction areas with limitations on placement on CMPP-listed mires and non-drained mires depending on the scenario. The GIS-analyses also provided peat extraction effects to net carbon storage levels, increase in the number of lakes in poor condition and mire areas in natural state suitable for berry picking. Calculable effects on mire species diversity were not available, where we needed to resort to qualitative description.

The baseline scenario in the survey was a peat-based bioeconomy scenario, where annual peat extraction would be increased 30% from its current level with high impacts to ecosystem services. Two versions of CMPP implementation scenarios (full and partial business-as-usual) were explored with no change to current annual peat extraction[1]. These two scenarios did not greatly differ on the GIS-calculated ecosystem services effects (i.e. other than biodiversity) and were thus considered as one scenario in the final survey. The final scenario is a biodiversity focused scenario, where peat extraction would decrease by 30% and economic activities would focus only on previously drained mires. These scenarios

[1] The respondents were informed that a business-as-usual peat extraction area would still require tripling the current production area, about 400 km^2, by 2050 to 1 200 km^2.

provided the range of the levels of the attributes varying in the choice situations (see section 3.3 Implementation of the CE).

Table 1. Descriptions of attributes in the choice experiment.

	Description
Climate effects, carbon storage	The peat and trees in peatlands bind carbon from the air. Peat production areas heavily release the stored carbon to the atmosphere accelerating climate change.
Peatland species diversity	Peatlands offer a habitat for species acclimatized to peatlands. Peat production destroys peatland species habitats.
Water quality	Peatlands with drainage leak humus and nutrients to downstream surface waters. These effects can cause local harm to water recreation and species living in water.
Area of peatland in natural state suitable for berry picking	Berry picking is allowed in peatlands regardless of protection status by everyman's rights. Significant edible berries growing in peatlands are cloudberry, cranberry and bilberry.
Effect peat production on the share of domestic fuels in energy production	In peat production the peatland requires drainage and the peat is extracted for fuel and seedbed. Peat is a domestic fuel and in the short term replaces coal burning from foreign sources.

The time-scale of scenarios was chosen to reach year 2050. While peatland area conversion to production area has immediate effects on the ecosystem, the recovery of used areas, if possible, may take decades (Metsähallitus, State Forest Enterprise 2016). Further, the long time-scale accounts for the need of replacing depleted peat production areas and the subsequent effects on ecosystem services.

3.2 Design of the choice task

Efficient experimental design was used to allocate the attribute levels to the choice tasks in the choice experiment survey (Rose & Blimer 2009). Generating an efficient design requires the specification of priors for the parameter estimates. First, we employed zero priors in the design for pilot survey, and used parameter estimates from the pilot study to construct the final experimental design. Second, in the final study we employed a Bayesian D-efficient design using Ngene (v. 1.0.2), taking 500 Halton draws for the prior parameter distributions. Bayesian designs take into account the uncertainty related to the parameter priors by specifying a mean and standard deviation for the prior. We generated 36 choice tasks, and blocked them into 6 subsets, which resulted in six choice situations presented for each respondent. In the final design the D-error was 0.097854.

3.3 Implementation of the CE

The CE was applied by focusing especially on the whole scale of ecosystem services from mires. In the survey the choice situation was introduced explaining the alternatives for mire use along with a map (figure 1):

"*In southern Finland (blue in the map) it can be chosen whether to increase peatland protection or peat production. Increasing protection will cause costs to the nation, as land owners are reimbursed for their lost options for land use. On the other hand, increasing peat production increases economic activity and may provide income for the nation. There are 1 650 square kilometers of open mires suitable for peat production in southern Finland, of which 9% is also valuable for protection.*"

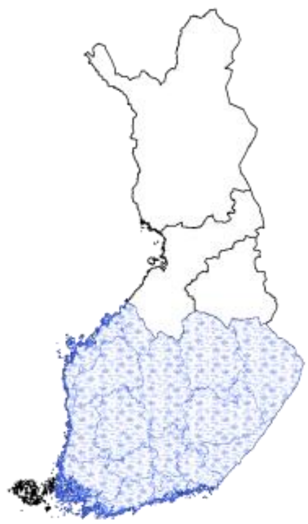

Figure 1. Southern Finland as represented in the survey to the respondents.

The respondents were motivated by explaining that the information acquired from the following choice situations helps decision-makers to guide the use of peatlands. Following a cheap talk reminder[2] on budget constraint and alternate uses of money including other

[2] A reminder on budget constraint and time scale of the effects also preceded each choice task.

nature protection, respondents were presented with choice situations comparing different options for the use of peatlands. The options have related benefits and drawbacks which begin to form in year 2017 and reach their full extent in year 2050. We assume that peatland use by agriculture and forestry remains as is, but the requirement for peat in energy production increases targeting unprotected, some also with high natural value peatland areas

Table 2 provides an example of a choice set, where option Y includes the best environmental state for each attribute and lowest peat production level, and option Z an intermediate level for each attribute. The status quo, or current development, has the worst environmental states for each attribute and the highest peat production level.

Table 2. An example of a choice set.

Which of the following options would suit you best in the absence of other options? Please remember that the money amount collected through taxes would be away from other consumption and that policy effects on mires begin immediately in 2017 reaching their full extent in year 2050.

		Situation in year 2050	
Effects on peatlands of southern Finland in 2050	**Current development**	**Option Y**	**Option Z**
Carbon storage decreases from current level (strengthening climate change)	12 %	6 %	9 %
Peatland species diversity	deteriorates significantly from current level	remains in the current level	deteriorates slighlty from current level
Number of poor water quality lakes increases by	100 lakes	10 lakes	70 lakes
Area of peatland in natural state suitable for berry picking	120 km^2	850 km^2	370 km^2
Change in the use of peat and share of domestic energy production	increases from current level, 13 % share	decreases from current level, 7 % share	remains in the current level, 10 % share
Effect on your taxes (*payment schedule treatment*)	0 € / year	Y € / year (in ten years altogether Y*10 €)	Z € / year (in ten years altogether Z*10 €)
I support this alternative	○	○	○

3.4 Payment schedule treatment

The payment schedule treatment was implemented within four subsamples with equal number of respondents. The payment schedule-subsamples presented in the choice tasks – a respondent received only one type of payment schedule in the questionnaire – were as follows:

1. Lump-sum payment: a single payment in 2017
2. 10 years annual payment (total sum informed) starting in 2017 and lasting until 2026
3. 10 years annual payment (total sum informed) starting in 2020 and lasting until 2029
4. 10 years annual payment (total sum informed) starting in 2023 and lasting until 2032

The lump-sum payment varied on scale 0, 10, 20, 50, 150, 200, 500 €. The same scale was used for annual payments in sub-samples 2, 3 and 4, implying total payments up to 5000 € over ten years as suggested to be shown to respondents by Egan et al. (2015). For the lump-sum payment, respondents were reminded that the payment will cover for the whole policy period.

3.5 Data collection

The choice experiment attributes were tested on a focus group of nine people in May 2016. The event was recorded and used to clarify and sharpen the texting in the questionnaire. The survey questionnaire was tested on a pilot survey of 204 respondents in June 2016. The final survey was gathered between August and October 2016 using an internet panel to ensure a nationally representative sample for the survey. The survey request did not inform respondents of the subject of the survey prior to opening the link to the questionnaire. The questionnaire was tested on both mobile and laptop environments to minimize technical bias in responses. The internet panel of Taloustutkimus Oy comprises over thirty thousand respondents who have been recruited to the panel using random sampling to represent the population (Taloustutkimus, 2017). After five reminders 1997 respondents completed the survey entirely giving a response rate of 18%. Table 3 shows the descriptive statistics of the full sample. In general, the survey sample is overrepresented by males, older population with above average education and income, and underrepresented by population with larger households.

Table 3. Descriptive statistics of the full sample

	Sample average
Age (mean)	52.16
Gender (% males)	54.7
Education level (college or higher, %)	56.8
Household size (equal or lower than 2 members, %)	70.4
Annual household income (over 50.000€, %)	50.8

4. Econometric models and discount rate

4.1 Random parameters logit model

A random parameters logit (RPL) model with interactions (Mc Fadden and Train, 2000; Train, 1998; Hensher & Greene 2003, Train 2003) performs well when researchers anticipate the sources of parameter heterogeneity. The model can be used to reveal preference variation in terms of both unconditional taste heterogeneity (random heterogeneity), and conditional heterogeneity (systematic heterogeneity) where individual characteristics or other factors of interest interact with choice-specific attributes and/or with the alternative specific constant (ASC) (Train 2003, Hensher et al. 2005).

The model assumes that coefficients β vary randomly across respondents, with distribution density $f(\beta)$. The probability of choosing an alternative over the choice set is a weighted average of the logit formula evaluated at different values of β. The weighting is based on the mixing distribution $f(\beta)$ that can follow any continuous distribution motivated by researcher's assumptions (e.g. positive or negative values only) and model fit. The most commonly applied distributions are the normal, triangular, uniform and lognormal (Hensher et al. 2005).

4.2 Generalized mixed logit model accounting for scale and taste heterogeneity

Scale heterogeneity refers to the variance of the variance term of utility over different choice situations (Greene and Hensher 2010). It reflects the presence of uncertainty in respondents' choices. The generalized mixed logit (GMXL) model extends mixed logit model to explicitly account for scale heterogeneity in the presence of preference heterogeneity.

GMXL is based on the specifications of mixed logit as these have been developed by Train (2003), Hensher and Greene (2003), Greene (2007) and Fiebig et al., (2010). The model (Hensher et al. 2015) embodies both observed and unobserved heterogeneity in the preference parameters of individual *i*:

$$\beta_i = \sigma_i[\beta + \Delta z_i] + [\gamma + \sigma_i(1-\gamma)]\Gamma_{v_i}, \text{ where}$$

$\sigma_i = exp[\bar{\sigma} + \delta h_i + \tau w_i]$ is the individual specific standard deviation of the idiosyncratic error term,

h_i is the set of individual's characteristics,

δ are the parameters of observed heterogeneity,

w_i is standard normally distributed unobserved heterogeneity,

$\bar{\sigma}$ is the mean parameter in the variance,

τ is the coefficient of unobserved scale heterogeneity, and

γ is a weighting parameter that shows how variance in residual preference varies with scale, $0 \leq \gamma \geq 1$.

The term Δz_i reflects the observed heterogeneity that originating from z_i set of M characteristics of individual *i,* while Γv_i reflects the unobserved heterogeneity originating from v_i vector of K random variables with zero means and unit variances. The model reduces to RPL when $\Delta = 0$ and Γ is diagonal (Greene and Hensher, 2010).

The scale parameter σ_i allows the introduction of the desired level of randomness in peoples' choices or, else, the level of uncertainty. The scale parameter can be individual-specific, where different individuals have larger or smaller idiosyncratic components as opposed to deterministic components of the utility function. Hence, the scale parameter varies across respondents, following a lognormal distribution with the new parameter τ reflecting the level of scale heterogeneity in the sample, i.e. $\sigma \sim LN(1,\tau)$.

The scale parameter weights the importance of the deterministic portion of a random utility model relative to the idiosyncratic portion. An increase in the scale parameter increases the relative importance of the deterministic portion of the utility function. As the scale parameter increases, respondents' choices appear less random from the econometrician's perspective. As a result, it influences the confidence intervals of WTP estimates. (Czajkowski et al., 2014; 2016).

4.3 Models allowing for correlated random parameters

Mixed logit models also allow accounting for correlatedrandom parameters. Under this specification, the model reports the Cholesky decomposition matrix that illustrates the presence of correlated alternatives due to correlated random parameters. In this case standard deviations are not independent and deviation parameters need to be decomposed into their attribute-specific deviations and attribute-interaction ones. The attribute-specific standard deviations in the decomposition matrix represent the amount of variance attributable to the random parameters when correlations have been removed. The standard deviation parameters, defined as attribute-interaction standard deviation, are attributable to cross-product correlations. The off diagonal elements of the matrix reveal the amount of cross-parameter correlations where large covariance signifies a substantial relationship between two random parameters.

4.4 Model specifications

As we expected conditional heterogeneity due to the different payment schedules in the split samples we used RPL modeling approach. We employed a RPL model including all cases as the baseline model. To further improve our estimations, GMXL model was used to cover scale heterogeneity in the presence of taste heterogeneity. Alternative specific constant (ASC) representing the status quo alternative was specified as a component of respondents' utility. All parameters were treated as random variables, following an unconstrained triangular distribution following earlier studies (Balcombe et al. 2009; Green and Hensher 2010). The choice distribution alleviates fat tail problems associated with normal and log-normal distributions.

Goodness-of-fit measures showed that the GMXL model performed better of the two, similar to earlier studies (e.g. Hensher and Greene 2017; Greene and Hensher 2010). Thus we continued using GMXL to extract information from each payment version. With the exception of the payment variable, all parameters were specified random under an unconstrained triangular distribution. The latter specification facilitates the calculation of

WTP estimates. As WTP from a mixed logit model is given by the ratio of two random distributions, the resulting WTP distribution has infinite moments and, hence, poorly defined mean and standard deviation (in Czajkowski et al. 2016). The same was confirmed by our findings during the process of analysis. A common response to the problem is to assume a fixed payment coefficient (Hole and Kolstad 2012). As both the RPL and GMXL baseline models revealed the payment parameter distribution to have minor, albeit significant, standard deviation, we assumed the parameter fixed in all version-specific GMXL models for convenience.

Parameter estimates of the RPL and GMXL models are based on simulation. Train et al. (2000) suggest several hundred random draws. To reduce computation time, the estimations were performed using intelligent draws. All models were estimated using NLOGIT 5, which offers two intelligent draws methods, i.e. standard Halton sequence and shuffled uniform vectors. Halton draws are more popular but may induce correlation noise across the space of draws (Hensher et al. 2015) whereas shuffling may reduce this noise. We ran GMXL for the lump-sum payment version using varying number of draws (100 to 2500) for both methods. We found the results more stable at 1500 shuffle draws. Baseline models were performed using 500 shuffle replications.

4.5 WTP calculation

Marginal willingness to pay for attribute levels were calculated using the estimated parameters of GMXL models for each split sample. The WTP estimate for a discrete improvement is provided by the ratio of the coefficient for any attribute β_i to the negative of the coefficient for the cost attribute β_c with all else remaining constant: MWTP = β_i / β_c (Louviere et al., 2000). We calculated the WTP for the best case choice set by using the sum of the MWTP for all attributes where all environmental attributes were set at their highest (best environmental) level and ASC was set at value zero.

4.6 Implicit discount rate calculation

We calculated implicit discount rates – rates that would make the respondents indifferent between choosing one time frame of payments over another – across the different payment scenarios using an iterative process equating their present values. First we assessed the implicit discount rate between the lump-sum WTP in year 2017 (V1) and ten-year WTP starting in year 2017 (V2). Next we estimated implicit discount rates between the ten-year payment schedules comparing the ten-year payment schedule starting in year 2017 to ones starting in 2020 (V3) and 2023 (V4), separately.

The implicit discount rate was assessed by choosing a discount rate that would minimize the difference between the present values of compared WTPs across versions. Specifically, for present values of WTP_{V1} and WTP_{V2} we chose r, the implicit discount rate, such that

$$\sum_{X=0}^{9} \frac{WTP_{V2}}{(1+r)^X} = WTP_{V1}.$$

Respectively, to find the implicit discount rate between the ten-year payment schedules we equated[3] present values of V2 and V3, and V2 and V4 as follows

$$\sum_{X=0}^{9} \frac{WTP_{V2}}{(1+r)^X} = \sum_{Y=0}^{12} \frac{WTP_{V3}}{(1+r)^Y},$$

$$\sum_{X=0}^{9} \frac{WTP_{V2}}{(1+r)^X} = \sum_{Y=0}^{15} \frac{WTP_{V4}}{(1+r)^Y}.$$

5. Results

Table 4 reports the probability for accepting an alternative choice by bid and payment schedule. Despite some noise around the tendency, the probability for accepting an offered bid or payment declines with higher offers. For the lump-sum payment version (V1), the proportion of acceptance reaches a high of approximately 60% for 10 €/year and a low of 22% for 200 €/year. For the majority of payments, the probability of acceptance does not differ statistically significantly across versions and the same high and low percentages are noticed at corresponding payment levels. With the exception of 100 € and 300 € bids, the probability of acceptance increases with prolonging the period of non-payment (V3 and V4). This baseline figure may indicate signs of payment insensitivity.

[3] Note that for V3 (V4) the first three (six) years are with zero payments.

Table 4. Probability for accepting the tax payment per version of the payment

	Lump-sum payment (V1)	*10 year payment/Starts in 2017 (V2)*	*10 year payment/Starts in 2020 (V3)*	*10 year payment/Starts in 2023 (V4)*	Sig.
Payment	Probability of accepting the payment (%)				
0	0,295	0,271	0,273	0,262	0,012
10	0,590	0,613	0,580	0,579	0,437
20	0,559	0,557	0,543	0,536	0,755
50	0,342	0,336	0,318	0,361	0,320
100	0,248	0,286	0,307	0,323	0,014
200	0,223	0,245	0,251	0,262	0,448
300	0,248	0,212	0,300	0,304	0,000
500	0,248	0,292	0,256	0,273	0,293

5.1 Taste and scale heterogeneity

Baseline models

Table 5 reports the results of the RPL and GMXL models. The models include all four payment version subsamples. Pseudo R^2 value as a measure of goodness-of-fit shows improvement when both taste and scale heterogeneity is accounted for. Further, Akaike Information Criterion (AIC) also indicates that the GMXL performs better than RPL.

In GMXL model all random parameter coefficients are statistically significant with values increasing alongside improved attribute levels. The ASC estimate weakly – the parameter is not significant – suggests higher utility from choosing other than the status quo option. The increased taxes payment coefficient is negative, as expected.

The systematic heterogeneity around the mean values of model parameters cannot be explained by the time frame of payment. Hence other sources of preference heterogeneity should be searched for. The τ parameter that expresses scale heterogeneity, i.e. the variance of the variance term of utility level, is significant pointing towards scale heterogeneity.

The model also reports the diagonal[4] elements of the Cholesky decomposition matrix and the standard deviation of parameter distributions (Table 8, appendix). The diagonal elements of the Cholesky matrix, specified as attribute-specific standard deviation (Table 8, appendix), represents the amount of variance attributable to random parameters without correlations. We find for almost all attributes significant presence of heterogeneity that does not originate from correlated parameters. Hence all individuals within the sample cannot be represented by the same sign for these attributes. When correlations are accounted for, the dispersion of all parameters, represented by the derived standard deviations, is statistically significant for all parameters. The ASC, in particular, shows large dispersion calling for further exploration of heterogeneity. The standard deviation of the tax payment coefficient is significant but of smaller magnitude in comparison with the coefficients of other attributes. The variance of payment under a triangular distribution is $\sigma^2/\sqrt{6}$, estimated approximately at 0.0001.

Table 5. Estimates of the RPL and GMXL models allowing for correlated parameters

	RPL with conditional taste heterogeneity and correlated parameters		**GMXL with conditional taste and scale heterogeneity and correlated parameters**	
	Coef.	Std.dev	Coef.	Std.dev
ASC				
Carbon storage_L1	1.17468**	.57933	-.57494	.81767
Carbon storage_L2	.65767***	.20367	.65419***	.23331
Species diversity_L1	.72824***	.22534	.55020*	.28483
Species diversity_L2	1.81176***	.22245	1.52635***	.30960
Water quality_L1	2.81647***	.29956	2.16822***	.43649
Water quality_L2	1.01469***	.22368	.86593***	.28566
Berry picking_L1	1.74424***	.25813	1.75096***	.36377
Berry picking_L2	.90798***	.16452	.80125***	.20078
Energy production_L1	.33922	.22706	.83445***	.29571
Energy production_L2	.75143***	.23926	.82397***	.29701
Taxes_L	.94669***	.26873	.93377***	.33536
Interactions (V1 is the reference)	Heterogeneity around the mean			
ASC*V2	-1.10953	.84695	-3.15295**	1.23195
ASC*V3	-.39070	.83011	.01291	1.12291
ASC*V4	.00206	.76680	-.62465	1.07699
Carbon storage_L1*V2	.26375	.29211	-.06368	.32606
Carbon storage_L1*V3	-.07531	.28145	.01764	.30170

[4] The off-diagonal elements of Cholesky matrix that represent the amount of cross-parameter correlations are not presented in this paper to save space.

Carbon storage_L1*V4	.10796	.27601	-.11265	.30355
Carbon storage_L2*V2	.11860	.33415	-.11182	.39325
Carbon storage_L2*V3	.13680	.30666	.14422	.36539
Carbon storage_L2*V4	.72287**	.31317	.54976	.37555
Species diversity_L1*V2	.00111	.31325	-.20141	.37174
Species diversity_L1*V3	.14780	.31383	.25874	.36965
Species diversity_L1*V4	.02669	.29440	-.02281	.35380
Species diversity_L2*V2	-.36821	.41938	-.57718	.52194
Species diversity_L2*V3	-.01736	.41769	-.01565	.51706
Species diversity_L2*V4	-.33574	.39664	-.34205	.49944
Water quality_L1*V2	-.56597*	.31147	-.56584	.36969
Water quality_L1*V3	-.33396	.32931	-.13051	.37757
Water quality_L1*V4	.23625	.29733	.16461	.36049
Water quality_L2*V2	-.63615*	.35784	-.81715*	.43775
Water quality_L2*V3	-.42517	.36019	-.09450	.43849
Water quality_L2*V4	.19098	.34149	.02977	.42293
Berry picking_L1*V2	-.35267	.21953	-.36322	.24871
Berry picking_L1*V3	-.14744	.21634	-.15290	.24660
Berry picking_L1*V4	-.23951	.22056	-.17878	.24916
Berry picking_L2*V2	-.47390	.31138	-.60918	.38868
Berry picking_L2*V3	-.27532	.32114	-.41667	.39264
Berry picking_L2*V4	-.25597	.30506	-.42266	.38292
Energy production_L1*V2	-.02615	.34662	-.47187	.39439
Energy production_L1*V3	-.10464	.34967	-.01827	.39781
Energy production_L1*V4	.36788	.32467	.00579	.37954
Energy production_L2*V2	-.28123	.39031	-.51995	.44857
Energy production_L2*V3	.02389	.38957	-.24869	.43536
Energy production_L3*V4	.39396	.36354	.02590	.43249
Taxes_L*V2	-.00190	.00151	.00056	.00160
Taxes_L*V3	.00108	.00146	.00094	.00148
Taxes_L*V4	.00575***	.00144	.00142	.00145
Tau (τ):scale heterogeneity parameter	-	-	0.863***	0.100
Gamma (γ):weighting parameter	-	-	0.994***	0.118
Sigma (σ):Mean parameter of scale variance	-	-	1.000	1.052
Chi-square (df)	8186.814 (126)		8544.469 (128)	
Log.Likelihood	-9070.165		-8891.338	
McFadden Pseudo R^2	0.311		0.325	
AIC/N	1.535		1.505	
Sample size	11982		11982	

Models by payment version

Table 6 reports the results of the GMXL models which were performed for each payment version. All parameters except payment were specified as random following an unconstrained triangular distribution. The high Pseudo R^2 values indicate sufficient goodness of fit for analysis. The ASC parameter is negative indicating a decrease in utility level when conservation of mire remains at the status quo level. Random parameters of almost all attributes are positive and statistically significant. The coefficient of (non-random) tax payment is negative and approximately at the same level for all yearly payment model versions, V2 to V4. For model 1 using the lump-sum payment schedule, the payment coefficient is slightly higher compared to the other model versions, showing payment sensitivity.

Table 6 depicts the scale heterogeneity which is revealed by τ parameter. The parameter is significant for all models indicating that scale heterogeneity is present even after accounting for correlated random parameters. The τ parameter is found at higher magnitude for V1 and V4 payment schedules, i.e. choices are less random. There the deterministic part of utility dominates over the idiosyncratic part. The decision to pay for mire conservation either today or in the distant (six years) future interestingly shows to entail less uncertainty than the decision to pay in the near future. The estimate of γ that determines how the variance of residual taste heterogeneity varies with scale ranges between 0 and 0.01, but is not statistically significant different from zero.

Table 9 (Appendix) shows the diagonal elements of the Cholesky decomposition matrix and the standard deviation of the parameter distribution. For ASC, carbon storage and biodiversity attributes the dispersion around the mean of parameter stems from heterogeneous preferences for the attributes *per se*. Accounted for correlations the heterogeneity shows significant for all choice attributes. Thus an uncorrelated specification appears an inappropriate approach.

Table 6. Estimates of GML allowing for correlated parameters and scale and taste heterogeneity

	Model 1: Responses of lump-sum payment schedule (V1)	Model 2: Responses of 10 year payment schedule from 2017 onwards (V2)	Model 3: Responses of 10 year payment schedule from 2020 and onwards (V3)	Model 4: Responses V for a 10 year payment schedule from 2023 and onwards (V4)
	Coefficient value (s.d.)			
Random parameters				
ASC	-3,69823*** (1,37854)	-4.83154*** (1.64200)	-4.54351*** (1.74316)	-4.66915*** (1.58970)
Carbon storage_L1	0,80822** (0,37057)	.62560* (.33781)	0.75760* (0.41307)	.57169 (.37280)
Carbon storage_L2	0,48398 (0,4493)	.51390 (.37319)	0.36446 (0.41821)	1.00740** (.50551)
Species diversity_L1	2,01284*** (0,43499)	1.43821*** (.47029)	1.78833*** (0.68983)	1.57247*** (.47254)
Species diversity_L2	3,00058*** (0,5958)	1.74001*** (.57770)	2.75240*** (0.96796)	2.27035*** (.68822)
Water quality_L1	0,80570* (0,42378)	.27071 (.30556)	0.77166 (0.47584)	.85782* (.45222)
Water quality_L2	2,25027*** (0,51848)	.98081** (.41947)	1.90600*** (0.73008)	1.92218*** (.58108)
Berry picking_L1	0,95411*** (0,27303)	.45495** (.22332)	0.84372** (0.37912)	.71176** (.30358)
Berry picking_L2	0,95822** (0,39151)	.20958 (.29069)	0.57135 (0.36839)	.76394** (.37569)
Energy production_L1	0,84555* (0,46361)	.40260 (.36261)	0.74087 (0.51981)	.81641* (.46488)
Energy production_L2	1,02372** (0,51637)	.62879 (.41917)	1.03087* (0.60555)	1.04414* (.55178)
Nonrandom parameters				
Taxes_L	-0.00590*** (0.0007)	-0.00511 (0.0009)	-0.00483 (0.0008	
	Scale heterogeneity			
Tau (τ):scale heterogeneity parameter	*0.785****	*0.514****	*0.709****	*0.870****
Gamma (γ):weighting parameter	*0.002*	*0.01*	*0.000*	*0.000*
Sigma (σ):Mean parameter of scale variance	*0.922*	*0.946**	*0.928*	*0.915*
Chi-square (df)	2263.798 (80)	2349.228 (80)	2307.743 (80)	2155.691 (80)
Log.Likelihood	-2157.346	-2114.631	-2128.782	-2224.583
McFadden Pseudo R^2	0.344	0.357	0.351	0.326
AIC/N	1.495	1.466	1.478	1.533
Sample size	2994	2994	2988	3006

5.2 WTP estimates and implicit discount rates

Table 7 summarizes the WTP estimates calculated from the unconditional estimates of GMXL models by version. The WTPs are calculated for a scenario providing the highest environmental benefits. We would expect that respondents would reveal lower overall WTP given a lump-sum payment agreement than a ten-year periodical one, especially as we showed the respondents the total sum in the latter case. Our findings indicate that overall WTP under periodical payment is much larger. Next, the implicit discount factor across the different payment scenarios is estimated. We see high implicit discount rate between the lump-sum payment and repeated periodical payment. Comparing the ten-year payment schedules, i.e. V2 (2017 onwards) vs. V3 (2020 onwards) and V2 vs. V4 (2023 onwards) we see a surprising effect. For the shorter difference in time the implicit discount rate is 1.22, whereas for the larger time difference the implicit discount rate is only 1.12. The same is observed when comparing V3 (2020 onwards) vs. V4 (2023 onwards) payment scenarios.

Table 7: Mean WTP estimates for GML per version models and estimates of implicit discount factor.

	WTP (in €)		**Implicit discount factor (1+r)**			
	Mean (median) total WTP	**Mean (median) WTP/year**	Model 1: Responses of lump-sum payment schedule (V1)	Model 2: Responses of 10 year payment schedule from 2017 onwards (V2)	Model 3: Responses of 10 year payment schedule from 2020 and onwards (V3)	Model 4: Responses V for a 10 year payment schedule from 2023 and onwards (V4)
Model 1: Responses of lump-sum payment schedule (V1)	1336.283 (1242.651)	-	-	2.36	1.53	1.31
Model 2: Responses of 10 year payment schedule from 2017 onwards (V2)	-	773.375 (940.83)	2.36	-	1.22	1.12
Model 3: Responses of 10 year payment schedule from 2020 and onwards (V3)	-	1389.479 (1380.614)	1.53	1.22	-	1.04
Model 4: Responses V for a 10 year payment schedule from 2023 and onwards (V4)	-	1551.629 (1548.52)	1.31	1.12	1.04	-

Note: ( )= median

6. Conclusions

Comparing four payment schedule sub-samples for mire protection in Finland, we find willingness to pay figures vary partly unpredictably between time treatments. The test between lump-sum and annual payment showed strong insensitivity to payment schedule implying the inability of respondents to differentiate between a series of payments and a lump-sum payment on the project. Similar to Brouwer at al. (2008) annual payments were on average across all alternative series significantly higher than one-time-off donations, suggesting a negative implicit discount rate.

Comparing ten-year payment schedules with three-year delays across different subsamples, we observe that the implicit discount rate for the intermediate three-year delay (1.16) is considerably larger than the one for a six-year delay. In fact, the six-year delay produces an implicit discount rate of less than 1.01 more in line with Kim & Haab (2009) who also find support for hyperbolic discounting.

As suggested by Egan et al. (2015) our study supports mental accounts for charitable giving as the accepted annual payment was slightly higher as the lump-sum payment. However, our analysis cannot answer whether there is an inherent disability of respondents to think about the future. Concerns of respondents not taking the valuation task seriously are not seen to be, at least different across the sub-samples. Where Egan et al. (2015) note that respondents may not be able to discount, we can conclude that at least their discount rates appear to be time frame dependent.

Our results confirmed the majority of the previous results about the difficulty of respondents to think about the time frame of payment. Following the conclusions of Egan et al. (2015) our results also emphasize the importance of bringing clearly out the implications of annual payment for total payment and stressing information of the payment period in cheap talk reminding respondents of their budget constraint for the entire payment period.

We calculated discount rates based on estimated WTPs. Another alternative that may be interesting attempt for modelling time dependent choice experiment in future is the joint estimation of discount rates and WTPs similar to Bond et al. (2009) in contingent valuation context. However, to make this approach feasible would demand simpler modelling approach than models allowing scale and preference heterogeneity. This might not be a problem, as we found only minor preference heterogeneity between the sub-samples of different payment schedules. Although the timing of the payment severely affected the net present value of WTP it did not influence on the relative importance of the attributes. Where we found scale heterogeneity present in all subsamples, the time frame of the payment was not the origin of the observed scale heterogeneity, thus the timing treatments created no more randomness of choices more than the other treatments.

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Appendix

Table 8. Standard deviation estimates of the RPL and GMXL models allowing for correlated parameters

	Attribute-specific standard deviation			
	Coef. (std.dev)			
ASC	6.37371***	1.21047	9.28619***	1.31264
Carbon storage_L1	2.54658***	.31991	.13012	.27740
Carbon storage_L2	1.87458***	.37732	.28335	.54473
Species diversity_L1	2.65174***	.39125	2.25371***	.42419
Species diversity_L2	.02741	.40983	2.22121***	.38079
Water quality_L1	2.88887***	.36515	1.14385*	.65243
Water quality_L2	1.39632***	.44807	2.41427***	.36855
Berry picking_L1	1.36105***	.44350	3.49413***	.39818
Berry picking_L2	2.33682***	.42680	1.10890**	.52666
Energy production_L1	2.87949***	.36614	.16277	.64372
Energy production_L2	3.78028***	.35933	1.16090**	.54900
Taxes_L	.00207	.00227	.00175	.00266
	Attribute-interaction standard deviation			
	Coef. (Std.dev)			
ASC	6.37371***	1.21047	9.28619***	1.31264
Carbon storage_L1	3.00472***	.34521	1.47439***	.43548
Carbon storage_L2	2.85644***	.40674	3.41128***	.32259
Species diversity_L1	3.83934***	.29812	2.51241***	.36144
Species diversity_L2	4.69090***	.33154	2.88169***	.38250
Water quality_L1	4.14465***	.45341	4.82457***	.46958
Water quality_L2	4.88264***	.48961	5.52795***	.52110
Berry picking_L1	3.56151***	.40700	4.40665***	.35469
Berry picking_L2	3.58716***	.46448	4.57068***	.47872
Energy production_L1	3.50205***	.41115	3.25717***	.41133
Energy production_L2	6.20401***	.40192	5.27442***	.48986
Taxes_L	.02678***	.00186	.01890***	.00170

Table 9. Standard deviation estimates of the GML model allowing for scale heterogeneity and correlated parameters

	Model 1: Responses of lump-sum payment schedule (V1)	Model 2: Responses of 10 year payment schedule from 2017 onwards (V2)	Model 3: Responses of 10 year payment schedule from 2020 and onwards (V3)	Model 4: Responses V for a 10 year payment schedule from 2023 and onwards (V4)
	Attribute-specific standard deviation			
ASC	17.2007***	11.3099***	18.1268***	17.2520***
Carbon storage_L1	3.43573***	4.02292***	3.36342**	3.22084***
Carbon storage_L2	4.99022***	3.64229***	6.62813***	7.18840***
Species diversity_L1	1.38265	.66920	1.56723	.29492
Species diversity_L2	2.11397*	3.30300***	4.16582***	1.54587
Water quality_L1	2.29622	1.41874	2.62442	6.60312***
Water quality_L2	.28138	3.20072**	.12014	1.17532
Berry picking_L1	1.35746	1.49090	.14631	.30271
Berry picking_L2	.51664	.13978	2.38554	2.75976
Energy production_L1	1.49024	.36107	.17122	.12804
Energy production_L2	0.34011	1.00751	.37715	.03960
	Attribute-interaction standard deviation			
ASC	17.2007***	11.3099***	18.1268***	17.2520***
Carbon storage_L1	3.83851***	4.29938***	3.40022**	3.70393***
Carbon storage_L2	7.26793***	4.06210***	8.29506***	7.92823***
Species diversity_L1	4.25247***	3.39115***	7.32924***	7.45936***
Species diversity_L2	5.54074***	6.49800***	9.04600***	10.4905***
Water quality_L1	8.49137***	4.66144***	7.04469***	9.44776***
Water quality_L2	8.69780***	5.76047***	9.60034***	10.9600***
Berry picking_L1	4.99073***	3.88235***	7.60510***	5.62514***
Berry picking_L2	5.76443***	4.69977***	6.71310***	7.29599***
Energy production_L1	7.60983***	2.46172***	6.02204***	6.60669***
Energy production_L2	11.6946***	5.29244***	7.66764***	10.4673***