



Modelling Strategies for Discontinuous Distance Decay in Willingness to Pay for Ecosystem Services

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Abstract

Distance decay is a well-known phenomenon affecting welfare measures of localized improvements in environmental quality. We focus on an often overlooked issue in the distance decay literature, namely the modeling of jump discontinuities, i.e. when the willingness to pay distance decay function makes a vertical jump up or down. In an empirical stated choice experiment concerning localized water quality improvements where a toll bridge presents a barrier in the landscape that causes a sudden jump in travel costs, we first estimate individual-specific willingness to pay. We then investigate distance decay in these obtained estimates. We find that the degree of distance decay depends on which type of ecosystem services respondents are primarily motivated by. Besides modelling distance decay with a range of commonly used parametric functional forms, we also test a nonparametric generalized additive model specification. We find only minor differences between the different distance decay specifications, with no generally superior model specification. The nonparametric approach tends to capture distance decay in WTP just as well as any of the parametric specifications, but without requiring the analyst to make assumptions concerning the functional form of the distance decay relationship.

Keywords Distance decay · Discrete choice experiment · Jump discontinuity · Generalized additive model · Preference heterogeneity · Water quality

1 Introduction

Distance is often treated as a well-behaved, continuous variable in economic models describing human behavior. However, human behavior and perceptions of the landscape do not conform to a continuum. Landscapes are discontinuous entities marked by barriers (Tilley 1994; Appleton 1996; Coeterier 1996). There are natural barriers such as rivers, mountains, lakes, and forests, as well as manmade barriers such as roads, railroads, fences,

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and buildings which essentially slice the landscape into sections. Examples of such sections which are meaningful to people are, e.g., an island, a town, a suburb, a neighborhood, a valley, a beach, a forest. The sections and boundaries provide both restrictions and pathways through and into the landscape. People may experience these sections as changing landscapes and the boundaries may represent physical barriers that increase the costs of traveling (Weng and Lu 2009).

From a mathematical point of view, landscape barriers and sections can be seen as frictions across the landscape. Failing to understand or recognize these different frictions, we are unlikely to understand the spatial contexts of human behavior and the values provided by the landscapes. When the relation between people's Willingness-To-Pay (WTP) for an environmental good and their distance to said good is unclear, advising environmental policymakers becomes challenging, e.g., when defining the extent of the market and when aggregating individuals' WTPs for use in cost–benefit analysis (Bateman et al. 2006). It is widely recognized that the physical consequences of environmental policies or projects are more often than not unevenly distributed across the landscape. Theory and empirical evidence would suggest that the location of environmental goods and services has significant bearings on the welfare that individuals obtain from these (Bateman et al. 2006; De Valck and Rolfe 2018; Hanley et al. 2003; Schaafsma et al. 2013). Welfare estimates of environmental quality changes are likely to be affected by several different spatial aspects such as the geographical size of the area or resource affected by the change, the geographical boundary within which the relevant target population is identified, and the availability of relevant substitutes and complements (Schaafsma 2015; Johnston et al. 2017a, b). These aspects are all related to the concept of distance decay which refers to the commonly observed tendency of welfare estimates to decrease as the distance between the environmental good and the individual increases (Bateman et al. 2006).

Distance decay is relevant to consider when addressing use values such as recreational values. However, it is less clear—from the point of view of economic theory as well as empirically—to what extent non-use values would be subject to distance decay (e.g., Bateman et al. 2006; Jørgensen et al. 2013; Schaafsma et al. 2013; Rolfe and Windle 2012; Bakhtiari et al. 2018). Hanley et al. (2003) found distance decay in both use and non-use values, but the decay was more rapid for use values.

When assessing the values of environmental goods and services, it is commonly found that individuals exhibit heterogeneous preferences for the often wide range of different ecosystem service outcomes that are affected by ecological changes caused by a new project or policy initiative. Different individuals are thus likely to be interested in and motivated by different ecosystem services (Boyd et al. 2016). While some respondents in the given context obtain utility mainly from regulating services (e.g., wildlife conservation, habitat provision, and nutrient recycling), others obtain utility primarily from cultural services (e.g., recreation, physical and mental well-being, and preservation of local livelihoods and lifestyles). The former likely holds significant non-use value components while the latter by definition is directly linked to use values. Since the value components (use and non-use) differ between the many final ecosystem services that are affected by the same underlying ecological or policy change, this raises the question whether distance decay functions will differ between groups of respondents that are particularly motivated by different ecosystem services. In the context of distance decay, De Valck et al. (2017) and De Valck and Rolfe (2018) conclude that to improve our understanding of the influence of heterogeneity of preferences across respondents, more research is warranted. Hence, notwithstanding the ambiguous findings in the literature concerning differences in distance decay for use and non-use values, we follow Hanley et al. (2003) and hypothesize that distance decay will

be more pronounced for respondents particularly motivated by cultural ecosystem services than for respondents motivated by other types of ecosystem services.

In distance decay analysis, welfare estimates are typically modeled parametrically as monotonic and continuous functions of distance (Holland and Johnston 2017). This requires the analyst to make assumptions concerning the functional form of the distance decay relationship. Though economic theory predicts the presence of a distance decay relationship, at least for use values, it does not provide any guidance regarding the functional form of the relationship (Kling 1989; Ferrini and Fezzi 2012). A wide range of functional form specifications have been empirically tested within environmental economics (e.g., Concu 2007), transportation (e.g., Beckmann 1999), and geography (e.g., Taylor 2010). Given that the relationships between distance and welfare measures will inevitably be case- and context-specific, the question of which functional form to assume is inherently an empirical one, with limited if any theoretical foundation (Ferrini and Fezzi 2012). As noted by Concu (2007, p. 178) “...a search for the best functional form is necessary”.

The analyst’s choice of functional form specification is, however, far from trivial. Assuming a functional form that is not supported by the data has been shown to lead to biased welfare estimates (Kling 1989). Even though measures of statistical fit may help to identify the functional form that best describes the data in a specific case, the identification will be made within a limited set of candidate functions determined by the analyst. While the common parametric assumptions concerning monotonicity and continuity may be appropriate in some cases, they are likely to be overly restrictive in others—implying a risk of biased welfare estimates (Bateman et al. 2006). Johnston and Ramachandran (2014) highlight that spatial patterns in non-market WTP may indeed be much more complex, e.g., in the presence of local patchiness and hot spots. This potentially renders the use of the commonly used parametric distance decay functions insufficient and misleading. Along the same lines, Jørgensen et al. (2013), Schaafsma et al. (2013) and De Valck et al. (2017) show that non-random spatial distribution of substitutes may also complicate distance decay patterns in WTP beyond what is accounted for when using the commonly used parametric distance decay functions.

Geographic barriers in the landscape, whether naturally occurring or in the form of manmade constructions, separating the individual from the utility-generating environmental good or service are likely to result in discontinuous distance decay patterns (Longley et al. 2005). In case such barriers are present, imposing a continuous distance decay function in the parametric model would likely generate biased welfare estimates (Ferrini and Fezzi 2012). These barriers can work on very different geographical scales, from a local gravel road with a low speed limit that only affects those living close by, to crossing between two islands with a ferry or using a toll bridge.

To avoid the parametric assumptions that are inherently necessary when implementing the typical parametric approaches to modeling distance decay, Ferrini and Fezzi (2012) suggest using Generalized Additive Models (GAM) instead. The non-parametric GAMs incorporate flexible, nonlinear and differentiable functions as smoothing terms to identify the functional form directly from the data, thus avoiding the otherwise necessary assumptions concerning model flexibility and functional form in the parametric modeling approach. Comparing the use of GAMs to more traditional parametric models used in non-market valuation studies involving distance decay, Ferrini and Fezzi (2012) find GAMs to provide better model fit as well as a reduced median WTP in a dichotomous choice contingent valuation (CV) study. Similarly, in a payment card CV study assessing the value of new urban parks, Andrews et al. (2017) find GAMs to produce lower welfare measures than standard parametric specifications.

As underlined by e.g. Schaafsma et al. (2012) and De Valck and Rolfe (2018) reliable estimation of the spatial distribution of welfare measures is essential for reliable welfare aggregation in environmental valuation. Given the lack of theoretical justification for a parametric specification of distance decay and the fact that GAM avoids this, it is somewhat surprising that the only applications of GAMs in environmental valuation distance decay contexts so far are Ferrini and Fezzi (2012) and Andrews et al. (2017). While both these applications are set in a CV context, Ferrini and Fezzi (2012) note that it would seem worthwhile to apply GAMs in a stated Choice Experiment (CE) setting.

We contribute to this literature by providing the first empirical test of the performance of GAM for modelling spatial welfare heterogeneity in a CE context, while at the same time taking preference heterogeneity for ecosystem services into account. We test the suitability of GAMs in a setting where common parametric assumptions concerning the shape of distance decay will often fall short, namely in an empirical case where the distance decay function is expected to show a clear jump discontinuity. Specifically, the case concerns welfare impacts of coastal water quality improvements in a specific geographic area. Respondents are sampled from the population on two islands, one close to the area of interest and the other one further away. The two islands are only connected by a toll bridge. We hypothesize that the toll bridge will cause a jump discontinuity in the distance decay of welfare measures due to the jump in travel costs. We test this using a range of standard parametric distance decay models as well as the non-parametric GAM.

A priori knowledge of barriers causing a jump discontinuity will be available in some empirical cases, but unavailable in others, and we therefore conduct our tests in two different “level of knowledge” scenarios. In the first scenario, we assume that the analyst has a priori knowledge of the barrier, i.e., the toll bridge. The analyst can thus utilize this knowledge when setting up empirical models, e.g., by estimating separate choice models for subsamples that are spatially separated by the jump or by simply incorporating a dummy variable in the parametric distance decay function to capture the jump discontinuity. In the second scenario, we assume that the analyst has no a priori knowledge about jump discontinuities being present. Hence, models will have to uncover the presence of the toll bridge entirely from the data with no auxiliary information from the analyst. While this scenario is artificial for our empirical case as the toll bridge is well known, it serves as an example of how well these models perform when jump discontinuities are present, but unknown to the analyst.

Furthermore, we use an experimental setup where respondents are classified according to which type of final ecosystem service they are primarily motivated by. Some of these are use value oriented, and thus sensitive to travel costs, while others are more non-use value oriented and likely less sensitive to travel costs. We hypothesize that the distance decay, and potentially also the impacts of the jump discontinuity, will differ across these different types of respondents.

The following section provides the methodological background, including econometrics. Section three elaborates on the experimental setup and the data collected while section four presents results. Finally, the last section provides conclusions.

2 Methodology

Similar to Campbell et al. (2009), Johnston and Ramachandran (2014) and Czajkowski et al. (2017), we utilize a two-stage modeling procedure to investigate our research questions by first modeling respondents’ preferences for location and level of water quality

improvements using a mixed logit (MXL) specification. This model allows for heterogeneity in preferences across respondents, and it enables estimation of individual-specific preference parameters through the derivation of the conditional distribution based on the sampled respondents' choices. Applying Bayes theorem to derive the expected ratio between the estimated water quality attribute parameters and the parameter estimate for the cost, individual-specific WTP estimates can then be extracted. As noted by Hensher et al. (2005), these individual-specific WTP estimates should not be considered as the individual respondent's unique set of preference estimates. Strictly speaking, they are rather same-choice-specific parameter estimates for the subgroup of respondents who made identical choices when faced with the same choice tasks. In the second stage, the individual-specific WTP estimates obtained in the first stage are explained using distance decay models. Here we explore a range of typically used parametric distance decay specifications as well as the non-parametric GAM specification, with a particular focus on the ability to capture jump discontinuities.

2.1 Choice Modeling (Stage 1)

A standard Random Parameter Error Component Logit (RPECL) model is used for extracting information about preferences from the observed choices made by respondents (e.g., Train 2009; Scarpa et al. 2005, 2008). Focus group interviews and a pilot test had indicated that preferences for the water quality and location attributes could be expected to be heterogeneous. Hence, these attributes are specified as normally distributed random parameters. A full variance–covariance matrix is specified to allow for correlation patterns across these random parameters (Train and Weeks 2005; Scarpa et al. 2008; Hess and Train 2017). The price parameter is treated as a fixed parameter, even though it implies a fixed marginal utility of income. While specifying a random parameter for the price parameter may be more behaviorally plausible, it is often associated with severe limitations for welfare estimation (Johnston et al. 2017a, b). For instance, the well-known fat tail problems of the lognormal distribution will lead to extreme observations of WTP, which would be detrimental to the second stage of our procedure.¹ An Alternative Specific Constant (ASC) is specified for the status quo alternative to capture the systematic component of a potential status quo effect. Furthermore, an error component additional to the usual Gumbel-distributed error term is incorporated into the model to capture any remaining status quo effects in the stochastic part of utility. The error component is implemented as an individual-specific zero-mean normal distributed random parameter assigned exclusively to the two experimentally designed alternatives. This is to allow for correlation patterns in utility over these alternatives, capturing any separate variance associated with the cognitive effort of evaluating experimentally designed hypothetical alternatives as opposed to the real-life status quo alternative (Hensher and Greene 2003; Scarpa et al. 2007, 2008). The utility structure can be formally described as:

$$U_{nij} = \begin{cases} V(ASC) + \varepsilon_{nij}, & j = 1 \text{ (Status quo)}; \\ V(x_{nij}, \tilde{\beta}_n, \beta, \mu_n) + \varepsilon_{nij}, & j = 2, 3 \end{cases} \quad (1)$$

¹ We did run a model with a lognormal specification for the price parameter which indeed confirmed the existence of a fat tail issue causing the individual specific WTP estimates to become much more dispersed and with a substantial number of severely inflated and improbable WTP estimates.

where the indirect utility, V , is a function of the vector of explanatory variables, x_{nij} , as well as the vectors of individual-specific random parameters, $\hat{\beta}_n$, and the fixed price parameter, β . For the two experimentally designed policy alternatives, the common individual-specific error component μ_n enters the indirect utility function, while the ASC replaces it for the status quo alternative. The unobserved error term ε_{nij} is assumed Gumbel-distributed. Individual respondents are denoted by n , while j denotes the alternative and t the choice set. The $\hat{\beta}_n$ varies over individuals in the population with density $f(\beta|\theta)$, where θ represents a vector of the unknown parameters to be estimated.

The specified RPECL model accommodates estimation of individual-specific estimates of preference parameters for each n . Following, e.g., Greene et al. (2004), Hensher et al. (2006) and Hess (2010), this is achieved by applying Bayes' rule to construct the conditional density for the random parameters of interest:

$$f(\beta_n|Y_n, X_n, \Omega) = \frac{f(Y_n|\beta_n, X_n, \Omega)f_\beta(\beta_n|\Omega)}{f(Y_n|X_n, \Omega)} \tag{2}$$

where Ω denotes the underlying parameters of the distribution of β_n . The sequence of choices made by individual n is denoted by Y_n , and X_n encompasses all elements of x_{nij} for all alternatives and choice tasks. The conditional mean can then be approximated for each random parameter by simulated maximum likelihood:

$$\hat{E}(\beta_n|Y_n, X_n, \Omega) = \frac{\frac{1}{R} \sum_{r=1}^R \hat{\beta}_{nr} \prod_{t=1}^T \frac{\exp(\hat{\beta}_{nr} x_{ntj})}{\sum_{k=1}^J \exp(\hat{\beta}_{nr} x_{ntk})}}{\frac{1}{R} \sum_{r=1}^R \prod_{t=1}^T \frac{\exp(\hat{\beta}_{nr} x_{ntj})}{\sum_{k=1}^J \exp(\hat{\beta}_{nr} x_{ntk})}} \tag{3}$$

where \hat{E} expresses the average of β for the individual n , over the $r = 1, \dots, R$ simulated draws.

Once the individual-specific β s are estimated for each of the random parameters associated with water quality and with the location, the individual-specific WTPs are calculated by simply dividing by (the negative of) the price parameter estimate. Obtaining the individual-specific WTP estimates is the main objective of the first stage of analysis, as these estimates will serve as dependent variable in the second stage of the analysis.

2.2 Distance Decay Models Explaining WTP (Stage 2)

The spatial distance decay of the estimated WTP from the choice models is investigated using both parametric and non-parametric models. The parametric models cover commonly used distance decay specifications where WTP is modelled as a linear, a log, an inverse or a squared function of the distance, d , to the good—see functions in Eq. (4). Furthermore, for each of the parametric models, we specify an additional model incorporating a dummy variable indicating whether the respondent lives on Zealand. This is intended to directly capture the potential jump discontinuity caused by the toll bridge between Zealand and Funen (see Fig. 2).² Models including this dummy variable are intended to reflect a scenario where the analyst has a priori knowledge of the jump discontinuity, while the parametric models excluding it are intended to reflect a scenario where such knowledge is not available to the analyst.

² As will be outlined in Sect. 4, the dummy parameter estimate may however also potentially be affected by other differences between Zealand and Funen.

$$\begin{aligned}
 WTP_n &= \varphi_1 d_n + \epsilon, & WTP_n &= \varphi_1 \log(d_n) + \epsilon, \\
 WTP_n &= \varphi_1 \frac{1}{d_n} + \epsilon, & WTP_n &= \varphi_1 d_n + \varphi_2 d_n^2 + \epsilon
 \end{aligned}
 \tag{4}$$

The parametric models are estimated using a Generalized Linear Model (GLM) setup. The non-parametric model is estimated using a GAM where the respondents' WTPs are explained as a smooth function over the geolocation of respondents. The location of respondents was geocoded based on the centroid of the postal code of the area in which they live. Distances were measured as the shortest possible road distance between this location and nearest entry point at the localized good.

The GAM is a special case of the GLM where a continuous explanatory variable can be treated non-parametrically in smoothing functions (Wood 2006). In this case, WTP is estimated as a function of the x, y coordinates of the respondent's location.

$$WTP_n = f(x_n, y_n) + \epsilon \tag{5}$$

In Eq. (5) f is the smoothing function over the x, y spatial coordinates of individual n . The smoothing function is made up of the sum of k thin plate regression spline bases, b_n , each multiplied by the coefficient $\alpha : f = \sum_{n=1}^k \alpha_n b_n(x, y)$. The thin plate bases consist of a series of complex polynomials which enter into the model similar to other explanatory variables. The α coefficient is estimated similar to regular parameters. Separately these smoothing parameters do not provide any useful information. However, combined they produce a data-driven functional form relationship with the dependent variable. In this case the smoothing function includes two variables which means that instead of a line, they describe a surface in x, y space (von Graevenitz and Panduro 2015). The advantage of the GAM is that the functional relationship is constructed with no a priori assumptions of the specific relationship between WTP and location. In contrast, traditional parametric models a priori restrict the functional form to a specific assumed relationship.

The smoothing function will capture more of the variance of the dependent variable with the increase of thin plate splines. However, with a large number of splines, the risk of overfitting increases. To reduce the risk of overfitting, a penalty of "wiggleness", θ , is included in the estimator. The penalty term enters into the object function as an additional term. The parameters of the model, described by B, are estimated based on the following expression.

$$\hat{B} = \arg \min_B 2(l_{max} - l(B) + \theta \int \int \left(\frac{\delta^2(f(\alpha))}{\delta x^2} + \frac{\delta^2(f(\alpha))}{\delta x * y} + \frac{\delta^2(f(\alpha))}{\delta y^2} \right) \delta xy \tag{6}$$

The first term of the equation is the deviance measure which measures the difference between the satiated likelihood, l_{max} , and the likelihood of the reduced model $l(B)$. The second term is the penalty on the variance of the second derivatives of the smoothing function over the x, y coordinates. The estimator therefore explicitly contains the trade-off between bias and variance, which reduces the risk of overfitting even with a large number of splines (von Graevenitz and Panduro 2015).

3 Experimental Design and CE Implementation

Denmark is characterized by an intensely farmed landscape with more than 60% of the landmass being used for agriculture. This agricultural intensity, combined with a relatively long coastline and shallow fjords, estuaries and coastal waters, has led to problems related to coastal eutrophication (Dalgaard et al. 2014). This has negative impacts on water quality and consequently on the wide range of associated ecosystem services. To address our research questions, we use empirical data³ from a CE study aimed at assessing the WTP for achieving good ecological status in Danish coastal waters in line with the targets of the EU Water Framework Directive (European Commission 2000).

Questionnaire development was based on three focus group interviews with lay audiences and two workshops with water quality experts. This provided valuable insights on the survey design in general as well as on potential preference heterogeneity in relation to different ecosystem services affected by water quality changes. The focus groups were conducted over a period of three weeks in February 2015. The focus groups were conducted in different regions of the country, covering both the capital region, a suburban region, and a rural region. For each focus group, participants were recruited using a local nominator ensuring variation in the group according to gender, age, and educational background. The final set of attributes and levels used in the design of policy alternatives are summarized in Table 1.

Choice tasks were generated using the Ngene software (ChoiceMetrics 2014), optimizing the experimental design for D-efficiency, assuming a multinomial logit model. The design was updated using priors obtained from a pilot study with 200 respondents drawn from the same sample frame as the main survey in March 2015. The optimization algorithm was stopped after running for 24 hours without identifying further design efficiency improvements. The resulting design consisted of a sequence of 12 choice sets per respondent, with no blocking involved. Each choice task consisted of two policy alternatives that would improve water quality in particular geographical areas, and a third alternative, namely the zero-cost status quo option with no water quality improvements. Input from the lay audience focus groups and expert workshops were used to construct and describe a 5-level water quality ladder, similar in concept to water quality ladders or indices used in previous stated preference surveys (e.g., Hime et al. 2009; Van Houtven et al. 2014; Walsh and Wheeler 2013). The approach follows the standard classification within the EU Water Framework Directive (European Commission 2000). An example of a choice task as it appeared in the questionnaire is shown in Fig. 1.

Poor ecological status is only considered an option in the status quo alternative since an improvement to the current water quality level is required according to the EU Water Framework Directive. Variations in WTP associated with improvements in different policy areas are modeled by including attribute level dummy variables for each of two policy areas, Lillebaelt and Limfjorden, relative to the third policy area, Oresund, which serves as a reference level. Figure 2 displays the location of the policy areas. Due to the design of the CE, dummies for policy areas are only included for alternatives with water

³ We use a subset of a bigger dataset that was first used in Jensen et al. (2019). The survey and data description provided in the current paper thus focuses mainly on data collection aspects of particular relevance for the research questions addressed here. For full details of the data collection, the reader is referred to Jensen et al. (2019).

Table 1 Attributes and levels used in the experimental design

Attributes and levels	Definitions and coding
<i>Water quality</i>	
Medium ecological status (reference level)	Binary (dummy) variable indicating whether the policy intervention results in medium ecological status; a value of 1 indicates that good water quality have been obtained. Levels: 0 or 1. Serves as reference level against which the two other water quality dummies are estimated in the choice model
Good ecological status	Binary (dummy) variable indicating whether the policy intervention resulted in good ecological status; a value of 1 indicates that good water quality have been obtained
Very good ecological status	Binary (dummy) variable indicating whether the policy intervention resulted in high ecological status; a value of 1 indicates that high water quality have been obtained
<i>Location of improvements (Policy area)</i>	
Oresund region (reference level)	Binary (dummy) variable indicating the geographic area of the policy intervention; a value of 1 indicates a water quality improvement in Oresund. Serves as reference level against which the two other policy area dummies are estimated in the choice model
Lillebaelt region	Binary (dummy) variable indicating the geographic area of the policy intervention; a value of 1 indicates a water quality improvement in Lillebaelt
Limfjorden region	Binary (dummy) variable indicating the geographic area of the policy intervention; a value of 1 indicates a water quality improvement in Limfjorden water catchment area
Cost	Continuous variable describing the increase in household income tax payments associated with the policy alternative. Household costs for the status quo alternative is zero. Levels: 45, 90, 180, 510, 1240, 2100 DKK ^a

^aThe levels for the annual household costs are approximately equivalent to €6, 12, 24, 69, 167, 282

quality improvements. Hence, WTP estimates for policy areas are conditional on some improvement of the current water quality.

To identify which type of ecosystem service each respondent was mainly motivated by, a series of questions consisting of nine attitudinal statements was developed based on a semi-quantitative Q-methodology analysis of the focus group interviews (Armatas et al. 2014). Each of these attitudinal statements were found to indicate preferences for a particular type of ecosystem services (Jensen 2019). Based on the nine attitudinal statements, three survey questions were developed in which the respondent had to choose a preferred statement among three competing statements. The statements and questions are provided in “Appendix 1”. Based on answers to these three questions, each respondent was sorted into one of four distinct groups. The first group was primarily motivated by improving conditions for habitats and biodiversity (regulating services). The second group was primarily motivated by improvements in recreational opportunities (cultural services). The third group was primarily motivated by improving conditions for the fishing industry (provisioning services). The fourth and last group contained remaining respondents who could not be classified as being motivated by any single type of ecosystem service.

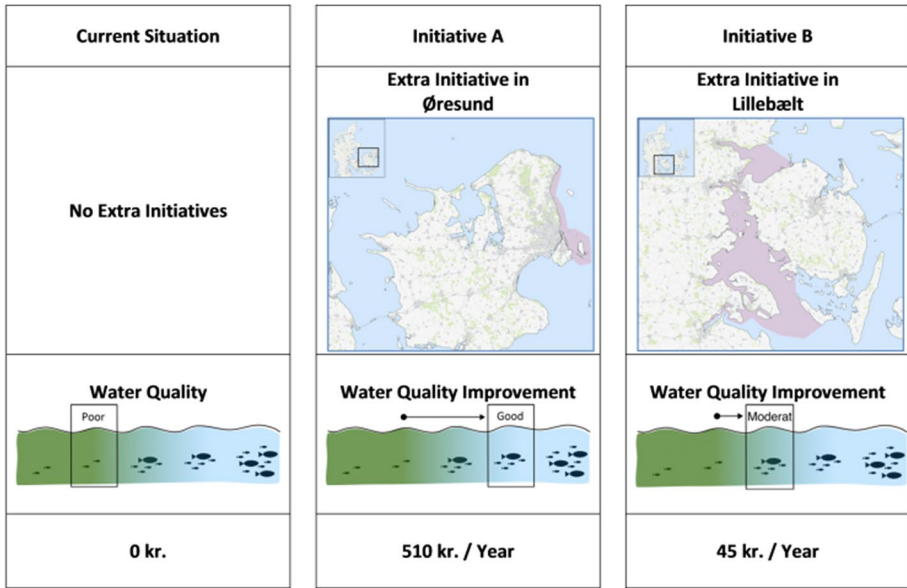


Fig. 1 Choice task example

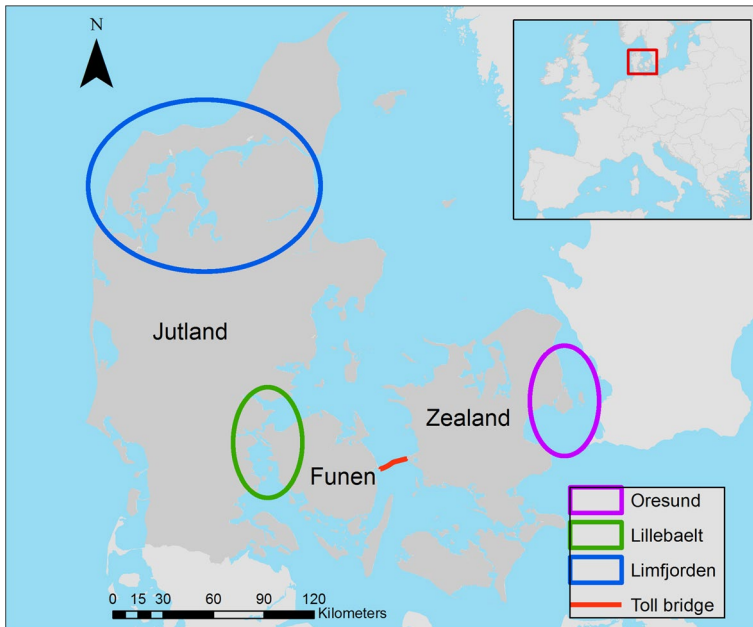


Fig. 2 Map of Denmark, outlining the sample areas as well as the policy areas and the location of the toll bridge between Funen and Zealand. The small insert in the upper right corner displays the location of Denmark in Europe

The CE data collection was conducted online during April and May 2015, using a pre-recruited panel maintained by a market research firm in Denmark. Sampling was stratified to ensure representativeness on age, gender, geography, and education. Follow-up reminders were sent 2 and 3 weeks after the first contact, resulting in a final response rate of 22%. Having identified and excluded protesters,⁴ a final sample of 1653 respondents living on Zealand and 408 respondents living on Funen was realized, i.e. a total of 2061 respondents providing 24,732 choice observations for the following analysis. The sample displays a wide variation in terms of spatial distribution and, thus, distance to the policy areas.

The original full dataset⁵ also included respondents from the rest of Denmark, but for specifically investigating jump discontinuities in distance decay, we use only the subset of respondents living on Funen and Zealand. The reason is that since these two islands are only connected by a toll bridge, we know that there will be a sudden jump in the relationship between travel costs and travel distance caused by the payment required for crossing the bridge. The price for crossing the bridge one-way was 235 DKK (~€31) at the time of data collection, with discounts available in the form of same-day return trips for 375 DKK (~€50). Furthermore, in our distance decay analysis, we choose to focus on a new policy scenario that improves the water quality in the Lillebaelt coastal area to good ecological status. The relevant aggregate WTP thus consists of the WTP for improving water quality from medium to good ecological status plus the WTP for moving the location of the water quality improvement (the policy area) from Oresund to Lillebaelt. Due to the reference attribute levels used in the choice models (see Table 1), the aggregate WTP measure of interest thus relates to a change from a baseline policy in which the water quality in the Oresund coastal area is improved to medium ecological status, to a new policy instead obtaining good ecological status in the Lillebaelt coastal area. The reason for focusing on this policy change is that Lillebaelt, which is located on the western coast of Funen, is relatively close to respondents living on Funen, while all respondents living on Zealand are further away—plus they would have to pay for crossing the bridge to visit the Lillebaelt coastal area. As is evident from Fig. 2, the opposite holds true for the Oresund coastal area. We note that this also implies that there is a natural correlation between the distance and the dummy variable for respondents living on Zealand. As mentioned in Table 1, a third location, the Limfjorden coastal area, was also included as a level in the policy area location attribute. However, since this is located in the northern part of Denmark, which may also be reached by ferry from Zealand, this is left out of the distance decay analysis in stage 2.

4 Results

To provide an overview of the sample as well as a brief comparison of the two subsamples of respondents located east and west of the toll bridge, Table 2 displays a selection of relevant sample characteristics. If the subsamples differ substantially in characteristics that affect WTP, then incorporation of the toll bridge in the subsequent modeling would capture

⁴ Protesters were identified as those always choosing the zero-cost status quo option and subsequently reasoning this with one of the following statements: “I’m against increases in my income tax”, “The polluter should pay” or “The government should pay”.

⁵ The entire dataset as well as full documentation of the original dNmark valuation study that generated the data is available in the ERDA repository at https://sid.erd.dk/cgi-sid/ls.py?share_id=dbvRvqoRrg.

Table 2 Selected characteristics of the sample

Variable	Sample		
	Funen	Zealand	Merged
Number of respondents	408	1653	2061
Mean gender (female = 0, male = 1)	0.51	0.54	0.53
Mean age (years)	49.5	50.3	50.1
Mean income category (increasing levels from 1 to 11) ^a	4.6	5.2	5.1
Mean urban (rural dweller = 0, urban dweller = 1)	0.50	0.72	0.68
Mainly motivated by cultural ES	27%	27%	27%
Mainly motivated by regulating ES	60%	63%	63%
Not motivated by cultural or regulating ES	13%	10%	10%
Mean distance to Lillebaelt (km)	21	152	125

Italics indicate that chisquare tests comparing distributions across Funen and Zealand revealed statistically significant differences

^aThe household income categories start from <100.000DKK (level 1), and increases in steps of 100.000DKK until reaching the final category of > 1.000.000DKK (level 11)

not only the jump in travel costs, but also these other differences between respondents living on Funen and Zealand.

Most of the sociodemographic variables, as well as the motivations for particular ecosystem services,⁶ are similar across the two subsamples, suggesting that any effects of the toll bridge on distance decay in the subsequent models would primarily be a consequence of the jump in travel costs. However, as indicated in Table 2, we do find significantly higher household incomes in the Zealand sample, and we also find a higher share of urban dwellers. Higher income should, according to economic theory concerning decreasing marginal utility of income, be associated with lower cost sensitivity, which would translate into generally higher WTP, *ceteris paribus*. Furthermore, as noted in Hassan et al. (2019), urban dwellers are often found to have higher WTPs than rural dwellers, and this might also translate into displacements of the distance decay relationship (Logar and Brouwer 2018). Hence, these observed demographic differences across the two islands would likely confound the effects of the toll bridge, potentially posing a limitation for our investigation. Essentially, any jump discontinuity observed at the bridge could thus potentially also be caused by these observed differences across the two islands. However, since the higher household income and the greater share of urban dwellers are located on Zealand, the effects on WTP would run counter to that of the sudden increase in travel cost for reaching the Lillebaelt area. In other words, while the increase in travel costs is expected to lead to generally lower WTPs for respondents from Zealand, the higher household income and the greater share of urban dwellers would have the opposite effect.

Underlining the potential relevance of distance in relation to individuals' WTP for localized water quality changes, Table 2 also documents the geographic fact observed

⁶ As very few respondents were classified as being particularly motivated by provisioning services, for modelling purposes we decided to merge this segment with the segment that did not appear to be motivated by any single particular ecosystem service.

Table 3 Choice model results for separate as well as full sample

	Model 1a Funen subsample		Model 1b Zealand subsample		Model 2 full sample	
	Mean	SE	Mean	SE	Mean	SE
<i>Fixed parameters</i>						
ASC (Status quo)	-1.812***	0.267	-3.042***	0.140	-2.770***	0.120
Price ^a	-2.550***	0.101	-1.947***	0.038	-1.936***	0.033
<i>Random parameters</i>						
Lillebaelt, β_1						
Mean	2.859***	0.177	-0.599***	0.052	-0.036	0.058
SD	2.785***	0.213	1.546***	0.060	2.033***	0.064
Limfjorden, β_2						
Mean	0.896***	0.096	-0.992***	0.059	-0.637***	0.051
SD	0.913***	0.145	1.789***	0.063	1.630***	0.056
Good WQ, β_3						
Mean	1.084***	0.142	0.491***	0.067	0.549***	0.054
SD	2.515***	0.175	2.039***	0.083	1.969***	0.085
Very good WQ, β_4						
Mean	1.906***	0.167	1.344***	0.085	1.402***	0.069
SD	2.913***	0.185	2.666***	0.108	2.525***	0.146
<i>Error component</i>						
Policy alternatives, μ_{23}	4.875***	0.350	4.423***	0.169	4.332***	0.149
<i>Random parameter covariances^b</i>						
$\beta_1\beta_2$	2.197***	0.463	2.767***	0.190	-3.275***	0.093
$\beta_1\beta_3$	2.118***	0.584	0.870***	0.168	0.589***	0.164
$\beta_1\beta_4$	1.121	0.615	1.034***	0.209	0.829***	0.197
$\beta_2\beta_3$	-0.042	0.149	1.057***	0.142	-0.931***	0.122
$\beta_2\beta_4$	-0.421***	0.188	1.261***	0.176	-1.180***	0.148
$\beta_3\beta_4$	6.599***	0.921	5.171***	0.369	4.716***	0.305
Number of respondents	408		1653		2061	
McFadden pseudo-R ²	0.433		0.382		0.376	
LL at convergence	-3051		-13,473		-16,959	

*** Indicates statistical significance at the 0.1% level

^aFor computational reasons all prices entered in the dataset have been rescaled with a factor 1/1000, hence price parameter estimates obtained from the parametric models should accordingly be divided by 1000

^bThe lower diagonal of the variance-covariance matrix is reported here. The covariances indicate whether parameter estimates for individuals along the distribution on one attribute are generally associated with the parameter estimates for the same individuals in the parameter space for a second attribute. Positive values suggest that individuals with relatively large parameter estimates for the first attribute also tend to have relatively large estimates for the second attribute, and vice versa (Hensher et al. 2005)

in Fig. 2, that the Funen subsample is much closer to the Lillebaelt area than is the case for the Zealand subsample. Since both Funen and Zealand are islands, this naturally entails that the distance to substitute coastal waters relative to the Lillebaelt coastal area

is smaller on Zealand. This may be one of the key drivers behind an observed distance decay.

4.1 Stage 1: The Choice Model

The choice model described in Sect. 2 is estimated for the two subsamples of respondents living on Funen and on Zealand, as well as the full sample. Results are reported in Table 3. All random parameters are assumed to be normally distributed, and the full covariance matrix is estimated in order to allow for all forms of correlation among the random parameters (Hess and Train 2017). All models were estimated using Nlogit 6. Parameter estimates were found to stabilize when using around 700–800 Halton draws for simulations, so we used 1000 Halton draws in all the models presented in Table 3.

While the utility coefficients as such are not the focus of this paper, a few remarks concerning the results in Table 3 are in place. The choice models fit well to the data, and almost all model parameters are highly significant. Though preferences are heterogeneous, the majority of respondents have positive preferences for improvements in water quality. At the mean, respondents have significantly stronger preferences for very good ecological status compared to good ecological status (95% confidence limits for the mean parameter estimates do not overlap). Combined with the fact that the random parameter covariances for good and very good ecological status are significantly positive in all samples, this suggests that respondents are generally sensitive to scope.

Given the focus of this paper, we are particularly interested in the utility coefficients associated with the policy areas, i.e. the geographical location of water quality improvements. Models 1a and 1b in Table 3 may indicate that distance decay could be present. While the vast majority of respondents on Funen have positive preferences for improvements in Lillebaelt (relative to Oresund), the opposite is the case for respondents on Zealand. This, however, could be caused by other differences between the two regions, and even if it to some extent is caused by distance decay, these results provide no indications regarding the functional form of the distance decay. This will be investigated more thoroughly in Sect. 4.2.

The models reported in Table 3 are used for generating the individual-specific WTP estimates (as outlined in Eq. 3) which serve as input for the second stage. Given the policy scenario of interest described above, the individual-specific WTPs used in the second stage are calculated as the sum of the parameter estimates for Lillebaelt and good ecological status divided by the price parameter estimate for each individual respondent.

4.2 Stage 2: Modelling Distance Decay

In the following models, the individual-specific WTP estimates extracted in stage 1 are explained by the road network distance to Lillebaelt. Distance decay is estimated using a range of parametric distance decay specifications (Eq. 4) as well as the non-parametric GAM (Eq. 5). Specifications with an additional income variable were tested but are not presented here as the income variable was found to be insignificant across all model estimations. Initially, this raised some validity concerns as we would normally expect higher income to lead to higher WTP as previously mentioned. We thus performed an income sensitivity validity check in the choice models. This confirmed the presence of the expected positive correlation between income and the cost parameter, in line with economic theory. However, it also revealed that respondents with relatively higher income tended to have

slightly lower preference parameter estimates for water quality improvements in the Lillebaelt area. Hence, when dividing the estimated individual-specific parameter for a water quality improvement with the cost parameter in order to calculate WTP, the two effects more or less offset each other. Alleviating the initial validity concerns, this is the likely explanation why we find no significant effect of income on the WTP for good water quality in the Lillebaelt area.

In total, nine different model specifications are tested given that each parametric distance decay model is estimated with and without the Zealand dummy variable. The models describe the distance decay in WTP for a new policy that would result in good ecological status in the Lillebaelt area relative to a baseline policy that instead would result in medium ecological status in the Oresund area. We run all nine models for three different segments of respondents; (1) those primarily motivated by cultural ecosystem services, (2) those primarily motivated by regulating ecosystem services, and (3) those not belonging to any of these two groups.

4.2.1 Utilizing a Priori Knowledge Concerning the Presence of a Jump Discontinuity

We first model distance decay using the individual-specific WTP estimates obtained from choice models utilizing the a priori knowledge that the toll bridge represents a jump discontinuity in travel costs, i.e., models 1a and 1b from the first stage. Tables 4, 5 and 6 summarize the model results. Figures 3, 4 and 5 in “Appendix 2” provide graphical illustrations of the estimated distance decay functions for the nine different model specifications and the three segments of respondents. The grey shaded areas illustrate the 95% confidence interval around each regression and the black dots indicate the estimated median WTP at the given distance. The horizontal axis is the distance in kilometers.

First of all, we note that the distance parameters are significant and of the anticipated signs, implying that there is indeed distance decay in WTP for improvements in the ecological status of water in Lillebaelt relative to Oresund. When comparing across respondent segments, results confirm our hypothesis that distance decay is more pronounced among respondents particularly motivated by cultural ecosystem services. Specifically, we find the strongest distance decay in the WTP for cultural services where, e.g., the linear specification shows distance decay of around 15 DKK/km, compared to 10 DKK/km in the regulating services segment and 9 DKK/km in the segment covering remaining respondents. Visual inspection of Figs. 3, 4 and 5 in “Appendix 2” further confirm that the distance decay functions have a steeper slope for the cultural services segment.

The Zealand dummy parameter, which is intended to explicitly capture the jump discontinuity caused by the toll bridge, is significant and negative in all the parametric distance decay models, and model fit generally improves significantly when adding this parameter. Again, the impact is strongest for the cultural services segment, for which the estimated parameter indicates a sudden vertical jump downwards in WTP of 1492 DKK in the linear specification. Though not significantly lower from a statistical point of view,⁷ the equivalent parameter estimate of around 835 DKK obtained in the linear model for the regulating services segment is substantially lower from a practical perspective, e.g., for use in applied cost–benefit analysis.

⁷ We note that this could be a result of type II error even though with 553 and 1292 respondents in the two compared segments the sample sizes would not be considered small.

Table 4 Distance decay models for cultural services segment

	GAM	Linear	Linear dummy	Log	Log dummy	Inverse	Inverse dummy	Squared	Squared dummy
Distance	***a	-15*** (1)	-5** (2)	-836*** (57)	-130 (143)	8524*** (1027)	472 (1095)	-29*** (5)	9 (13)
Distance ²								0.08*** (0.03)	-0.05 (0.05)
d_Zealand			-1492*** (343)		-1846*** (345)		-2095*** (162)		-2085*** (648)
Constant	-70 (53)	1738*** (130)	1728*** (127)	3731*** (263)	1993*** (414)	-274*** (66)	1590*** (155)	2094*** (173)	1491*** (254)
N	553	553	553	553	553	553	553	553	553
Adj,R ²	0.32 ^b	0.30	0.32	0.28	0.32	0.11	0.32	0.31	0.32
LogLikelihood	-4735	-4741	-4733	-4747	-4734	-4807	-4735	-4737	-4733
LR-test ^c		12.60***	-	25.22***	-	144.68***	-	5.06**	-
UBRE ^d	1,595,779	1,632,072	1,583,510	1,669,729	1,593,061	2,072,374	1,594,905	1,609,996	1,585,911

Standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

^aThe smoothing function consists of a number of flexible and non-linear differentiable functions or splines. This is non-parametric and therefore does not produce coefficient estimates. Instead, asterisks denote whether the smoothing significantly reduces the deviance of the model

^bProportion of variance explained

^cTesting whether GAM LL is significantly higher (less negative) than LL for the nested model. Thus, no value reported when Gam LL is lower than the nested model. Degrees of freedom for evaluating the LR-test value in the chi-square distribution are calculated as the difference in number of parameters in the nesting and the nested models. The GAM model has the equivalent of three parameters as the so-called effective degrees of freedom (edf) for the smoothing function term is two and the constant adds one

^dUBRE (Un-Biased Risk Estimator) is used for model-selection and estimation of smoothing parameters in GAMs. UBRE is essentially a rescaled AIC measure. Hence, smaller values indicate better fitting models. UBRE can also be computed for GLMs, enabling comparison between GAMs and GLMs. For further details, see Wood (2006)

Table 5 Distance decay models for regulating services segment

	GAM	Linear	Linear dummy	Log	Log dummy	Inverse	Inverse dummy	Squared	Squared dummy
Distance	*** (1)	-10*** (1)	-4** (2)	-593*** (41)	-261** (104)	4681*** (594)	1052* (635)	-22*** (3)	-14 (9)
Distance ²								0.06*** (0.02)	0.04 (0.03)
d_Zealand			-835*** (243)		-829*** (239)		-1299*** (105)		-434 (444)
Constant	501*** (37)	1727*** (92)	1709*** (92)	3237*** (191)	2375*** (313)	401*** (41)	1532*** (99)	2034*** (127)	1892*** (193)
N	1292	1292	1292	1292	1292	1292	1292	1292	1292
Adj.R ²	0.15	0.14	0.15	0.14	0.15	0.05	0.15	0.15	0.15
LogLikelihood	-11,115	-11,117	-11,112	-11,117	-11,112	-11,185	-11,114	-11,112	-11,112
LR-test		4.60	-	4.44	-	140.26***	-	-	-
UBRE	1,734,110	1,740,246	1,727,055	1,740,049	1,726,560	1,932,921	1,731,288	1,726,781	1,728,182

Standard errors in parentheses. See notes in Table 4 for further explanations

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6 Distance decay models for segment covering remaining respondents

	GAM	Linear	Linear dummy	Log	Log dummy	Inverse	Inverse dummy	Squared	Squared dummy
Distance	***	-9*** (2)	-1 (4)	-573*** (104)	-147 (249)	5411*** (1537)	1778 (1647)	-25*** (9)	-5 (21)
Distance ²								0.08* (0.04)	0.02 (0.08)
d_Zealand			-1264** (595)		-1063* (565)		-1229*** (265)		-1087 (1054)
Constant	-187* (100)	913*** (228)	874*** (226)	2387*** (477)	1283* (754)	-323*** (112)	707*** (246)	1316*** (313)	957*** (468)
N	165	165	165	165	165	165	165	165	165
Adj.R ²	0.16	0.15	0.16	0.15	0.17	0.06	0.17	0.16	0.16
LogLikelihood	-1418	-1418	-1417	-1417	-1417	-1425	-1416	-1417	-1418
LR-test	-	-	-	-	14.00***	-	-	-	-
UBRE	1,691,291	1,685,443	1,660,127	1,672,387	1,656,941	1,844,671	1,648,620	1,670,647	1,680,378

Standard errors in parentheses. See notes in Table 4 for further explanations

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

The four distance transformations used in the parametric models assume different relations between distance and WTP. Except for the model specifying inverse distance, model performance is similar, e.g., considering R^2 or LogLikelihood measures. Differences in model fit across model specifications are most pronounced in the cultural services segment in Table 4. This was also the segment exhibiting the strongest distance decay. Across all specifications and segments in Tables 4, 5 and 6, we note that the simple linear distance decay model with a dummy variable to capture the jump discontinuity is among the best performing models, though differences in model fit are generally small.

The non-parametric GAM approach is persistently among the best performing models when considering model log likelihoods, UBRE, and proportion of variance explained as indicated by the adjusted R^2 . Especially for the cultural services segment, it is worth noting that the LR-tests in Table 4 indicate that GAM significantly outperforms all the parametric specification models when the Zealand dummy is not included to explicitly capture the jump discontinuity in these models. Hence, in our empirical case GAM seems to offer an approach to account for distance decay that is just as good as any of the commonly used parametric approaches—but without requiring the analyst to make restrictive assumptions about the distance decay relationships. Visual inspection of the graphical representations of the distance decay functions in “Appendix 2” confirms that GAM captures the variation in WTP over distance just as well as any of the parametric specifications.

4.2.2 A Priori Knowledge Concerning Jump Discontinuity is not Available

To test the importance of prior knowledge concerning the presence of a jump discontinuity, we re-ran all models in Sect. 4.2.1 using the individual-specific WTP estimates obtained from the choice model based on the merged sample, i.e., model 2 in Table 3. In other words, this analysis scenario pretends that we are not aware of the toll bridge. While artificial in our case, it serves the purpose of mimicking a common situation for analysts applying CEs in practice. Results reported in tables and graphs equivalent to those in Sect. 4.2.1 and in “Appendix 2” are provided in “Appendix 3”. To enable full comparison, this includes models incorporating the Zealand dummy variable even though this would not be relevant if the discontinuity was truly unknown. These models generally still find distance decay in the individual-specific WTP estimates. This is indicated by the significant distance parameters in the models and the downward slope of the distance decay functions in the graphical representations. However, the jump discontinuity is much less evident in these results than in the previous section. Furthermore, the jump is much less pronounced in the graphical representations of the distance decay functions. Hence, it would seem that the distance decay models are incapable of uncovering the jump discontinuity unless it is directly controlled for in the estimation of WTPs. Model-wise, the non-parametric GAM still performs just as well as the best of the parametric models when considering R^2 and LogLikelihood. The graphical illustrations leave the impression that GAM is similarly incapable of uncovering the jump discontinuity.

4.3 Consequences for Aggregate Welfare Measures

To assess the potential impacts of the different distance decay modeling assumptions on policy advice, we calculate the aggregate welfare measure of a policy scenario for the entire region based on the assumption that a priori knowledge of the toll bridge is utilized, i.e., based on Sect. 4.2.1. The proposed policy used as an example here involves improving

water quality in the Lillebaelt area to good ecological status instead of improving water quality in the Oresund area to medium ecological status.

We calculate the aggregate welfare measure using all nine distance decay models for all three respondent segments. Results are reported in Table 7. The user segment WTPs and distance decay functions are applied to the entire population of 2.7 million people living on Zealand and Funen. Table 7 reports the aggregate welfare measure for each segment as well as the total aggregate welfare measure calculated as the sum of the three segments. This aggregation is based on the segment proportions found in Table 2. For comparison, the last row reports aggregate welfare measures obtained when distance decay is completely disregarded.

The regulating services segment obtains a positive welfare measure equivalent to just above 800 million DKK, similar across all models. For the cultural services segment, the proposed policy results in a negative welfare measure, around –100 million DKK, but here we find slightly greater differences across model specifications. This is likely due to distance decay being more pronounced in this segment than in the other segments. Realizing that more people live in Zealand than on Funen, it is not surprising that the aggregate welfare measure for this segment is negative. Rather than an improvement from poor to good ecological status in Lillebaelt, the majority of these people would likely prefer water quality to improve from poor to medium ecological status in Oresund which is close by and, thus, easier and cheaper to reach for the recreational purposes that are particularly important for this group of people. On the other hand, people who are more interested in regulatory services on average care more about water quality improvements, than where they occur. Hence, for these people the fact that somewhere the ecological status is increased from low to high instead of low to medium is more important than the fact that the change is happening further away. This explains why the aggregate welfare measure for this group is positive even though distance decay does affect WTP and most people live on Zealand—the negative impact of distance is simply dominated by the positive impact of the larger improvement in water quality.

The total aggregate welfare measure calculated from the different distance decay models vary from 644 million DKK to 754 million DKK. Though not significantly different according to the largely overlapping confidence intervals, these differences could potentially matter for conclusions if e.g. used in cost–benefit analysis. Hence, the choice of distance decay modeling approach is not trivial in this respect. Furthermore, compared to the last row in Table 7 which reports the simple non-parametric mean, i.e., assuming no distance decay, it is evident that distance decay, in general, is important to take into account when generating this kind of policy advice. Most of the distance decay specifications produce total aggregate welfare measures for the proposed policy change close to 645 million DKK, which is around 15% lower than when distance decay is ignored.

5 Conclusion

There is good reason to suspect that distance decay in WTP for environmental goods is not continuous. In this paper, we show that barriers in the landscape, here represented by a toll bridge, may result in discrete jumps in the distance decay function. We furthermore show that the aggregate welfare measures are sensitive to the analyst's choice of whether and how distance decay is accounted for.

Table 7 Aggregate welfare measures in million DKK per year (95% confidence limits^a in brackets)

Model type	Segment 1: regulating services	Segment 2: cultural services	Segment 3: others	Total
GAM	832.0 [628.2, 1037.1]	- 129.9 [- 255.3, - 6.4]	- 57.7 [- 125.2, 9.6]	644.4 [247.7, 1040.3]
Linear	829.4 [663.0, 997.0]	- 128.2 [- 232.3, - 25.9]	- 57.1 [- 114.3, - 0.2]	644.1 [316.4, 970.9]
Linear (dummy)	829.9 [625.7, 1035.3]	- 127.7 [- 254.4, - 2.9]	- 56.6 [- 125.3, 11.8]	645.6 [246.0, 1044.2]
Log	841.5 [678.4, 1005.7]	- 117.2 [- 218.9, - 17.3]	- 52.9 [- 108.4, 2.3]	671.4 [351.1, 990.8]
Log (dummy)	836.6 [647.3, 1026.9]	- 118.7 [- 236.5, - 2.7]	- 53.9 [- 116.8, 8.6]	663.9 [294.0, 1032.8]
Inverse	875.8 [726.6, 1025.4]	- 77.7 [- 176.9, 20.2]	- 44.0 [- 94.3, 6.2]	754.1 [455.4, 1051.8]
Inverse (dummy)	831.0 [653.5, 1009.4]	- 114.7 [- 228.8, - 2.4]	- 53.1 [- 113.1, 6.5]	663.2 [311.7, 1013.4]
Squared	829.4 [620.4, 1039.6]	- 128.4 [- 257.6, - 1.1]	- 56.6 [- 126.6, 13.2]	644.4 [236.2, 1051.7]
Squared (dummy)	831.3 [601.1, 1062.6]	- 128.3 [- 271.1, 12.4]	- 56.9 [- 133.2, 19.2]	646.0 [196.8, 1094.2]
Simple mean (no distance decay) ^b	871.8	- 70.7	- 42.4	758.8

^aConfidence limits are calculated based on standard errors obtained from the models within each segment

^bConfidence limits not reported here since this is a simple non-parametric mean

We use a common two-stage process to investigate distance decay in the WTP for localized water quality improvements. In the first stage, we estimate individual-specific WTPs based on a typical choice model. In the second stage, we model the variation in these individual-specific WTPs by incorporating distance between the respondent and the good as an explanatory variable. Confirming findings in several previous studies, we find that WTP does indeed decay as distance increases. Testing a range of distance transformations commonly used when assuming some functional form of the distance decay in parametric models, we find that a simple linear specification performs well.

Inspired by Ferrini and Fezzi (2012), we also test the non-parametric GAM approach which based on smoothing terms identify the functional form of the distance decay directly from the data. This approach is somewhat similar to the spatial expansion method used in Schaafsma et al. (2013) and Cameron (2006) which essentially also smoothes over distance to allow for multi-directional spatial patterns. However, a linear relationship is assumed for the distance between the spatial coordinates in these applications. In this respect, the GAM is more flexible. The chosen approach was also inspired by recent developments in the hedonic house price models literature where the spatial coordinates of properties have been used to capture spatial omitted variable bias (e.g. Panduro et al. 2018; von Graevenitz and Panduro 2015). Overall, for our empirical case, we find the GAM approach capable of capturing the distance decay relationships just as well as any of the parametric models. Given that GAM avoids having to make functional form assumptions concerning the ‘true’ distance decay relationship—which not only lacks theoretical foundation but also introduces a risk of biasing welfare estimates if making the wrong assumptions—this would, in line with Ferrini and Fezzi (2012), suggest that GAM presents a useful alternative to the parametric approaches that are more commonly used to incorporate distance decay in WTP for non-marketed environmental goods.

Realizing that water quality changes lead to a wide range of changes in different ecosystem services, some of which are associated with use values while others are more associated with non-use values, and people are likely to have heterogeneous preferences for these ecosystem services, we identify three distinct segments of respondents. The first segment is particularly interested in and motivated by regulating ecosystem services, while the second segment is rather motivated by cultural services. The third segment covers respondents not identified as belonging to any of the first two segments.

In line with Hanley et al. (2003) and Bateman et al. (2006), we initially hypothesized that distance decay would be relatively more pronounced in the cultural services segment which for our empirical case is arguably the most directly linked to recreational use values, whereas regulating services to a greater extent would also encompass non-use values. Though differences are not statistically significant across all model specifications, our results are generally supportive of this hypothesis. This is further supported by visual inspections of the graphical illustrations of distance decay, which generally exhibit a steeper slope for the cultural services segment. As a consequence of this, we find that the choice of distance decay modeling approach has the biggest impacts on estimated welfare measures, and thus obtained policy advice, for this particular segment of the population. This, however, should be considered case-specific as cultural ecosystem services cannot generally be said to be more strongly associated with use-values than other ecosystem service categories.

A more novel investigation in our paper concerns the modeling of jump discontinuities. We utilize an empirical case, where the presence of a toll bridge between two islands presents a clear and well-known jump discontinuity in travel costs. Hence, a discontinuous downwards shift in the distance decay function is expected. Utilizing our a priori knowledge regarding

the presence of the toll bridge in the first stage of our procedure, we estimate separate choice models for the two samples of respondents living on one of the two islands. In the second stage, the parametric distance decay models are generally capable of capturing and confirming the jump discontinuity when a dummy variable for the toll bridge is incorporated explicitly in the model. The non-parametric GAM approach performs neither better nor worse than these models.

In practice, CE analysts often do not have solid a priori knowledge concerning geographical barriers in the landscape that may lead to jump discontinuities in WTP. We thus re-ran the first stage choice model on a single, merged dataset, essentially disregarding our knowledge of the toll bridge and instead treating respondents from the two islands as one sample. Using individual-specific WTPs from this choice model made it much harder for the models in the second stage to capture the jump discontinuity. Some of the parametric models with a dummy variable incorporated did recover a jump discontinuity caused by the toll bridge, but at the expense of the rest of the distance decay function not fitting particularly well to the data.

An important limitation in our empirical case is that the population on the two islands differ in other aspects than merely the presence of the toll bridge. Specifically, people on the island that is farther away from the environmental good on average have significantly higher income and are more prone to living in urban areas. Both aspects are likely to affect WTP and may thus be confounding the effect of the toll bridge in terms of driving the distance decay jump discontinuity. While we are unable to disentangle these effects in our empirical case, we note that both these effects would be expected to cause an upwards jump discontinuity in the distance decay function, i.e., the opposite directional impact as that of the toll bridge. Since our models do find a significant downwards jump discontinuity, we conclude that these confounding effects are at least not offsetting the effect of the toll bridge. Had we been able to control for these other differences, we would most likely just have found an even bigger jump discontinuity caused by the toll bridge.

Ferrini and Fezzi (2012) suggested that the non-parametric GAM approach could be beneficial in a CE context. We provide a first effort in this direction by employing a two-stage procedure and with a particular focus on addressing potential differences in distance decay patterns for segments of people who differ in their interests in different ecosystem services categories. A logical next step for future research is the possibility of setting up a simultaneous modelling approach, incorporating the GAM directly in the choice models rather than using a two-stage procedure. Further research should also be dedicated to investigating the performance of GAM in the presence of more complicated non-continuous distance decay patterns such as spatial patchiness and hot spots.

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Appendix 1: Statements and Questions used for Classifying Respondents According to Their Main Ecosystem Service Motivation

Motivation (ecosystem service)	Significant distinguishing statements
Biotic conditions (regulating)	<p>The conditions in and around coastal waters must ensure biodiversity conservation in terms of diversity of animal and plant species</p> <p>The conditions in and around coastal waters must support nutrient recycling</p> <p>The conditions in and around coastal waters must ensure good living conditions for animals and plants</p>
Conditions for recreation and lifestyle (cultural)	<p>The conditions in and around coastal waters must provide physical and mental well-being</p> <p>The conditions in and around coastal waters must preserve livelihood and lifestyle in the area</p> <p>The conditions in and around coastal waters must support recreational activities such as hiking, beach trips and picnicking</p>
Conditions for the fishing industry (provisioning)	<p>The conditions in and around coastal waters must secure commercial fisheries</p> <p>The conditions in and around coastal waters must ensure industrial production in the area</p> <p>The conditions in and around coastal waters must ensure water based production of e.g. mussels</p>

Question 1:

Which of the following conditions in and around coastal waters is most important to you?

- The conditions in and around the aquatic environment must conserve livelihood and lifestyles in the area
- The conditions in and around coastal waters must ensure biodiversity conservation in terms of diversity of animal and plant species.
- The conditions in and around coastal waters must secure commercial fisheries.

Question 2:

Which of the following conditions in and around coastal waters is most important to you?

- The conditions in and around coastal waters must ensure industrial production in the area
- The conditions in and around coastal waters must preserve livelihood and lifestyle in the area
- The conditions in and around coastal waters must support nutrient recycling

Question 3:

Which of the following conditions in and around coastal waters is most important to you?

- The conditions in and around coastal waters must support recreational activities such as hiking, beach trips and picnicking
- The conditions in and around coastal waters must ensure water based production of e.g. mussels.
- The conditions in and around coastal waters must ensure good living conditions for animals and plants

Appendix 2: Graphical Illustrations of Estimated Distance Decay Relationships when a Priori Knowledge Concerning the Presence of a Jump Discontinuity is Utilized

See Figs. 3, 4 and 5.

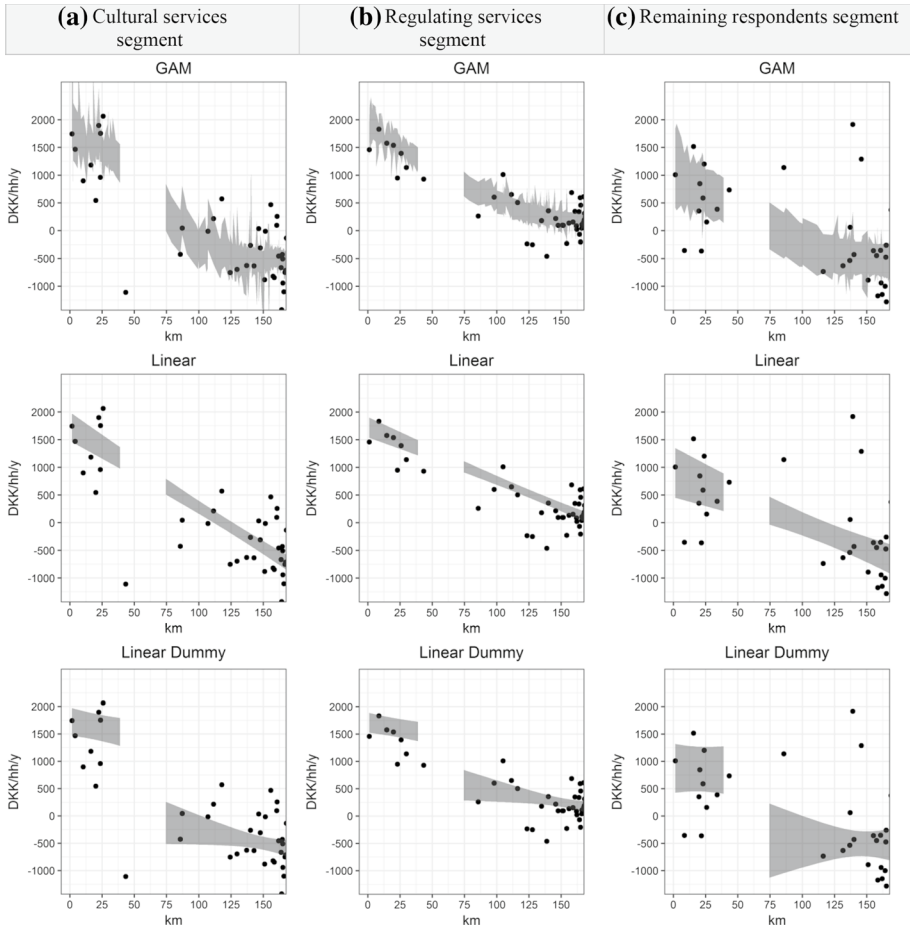


Fig. 3 Distance decay in WTP (GAM, Linear and Linear with dummy specifications)

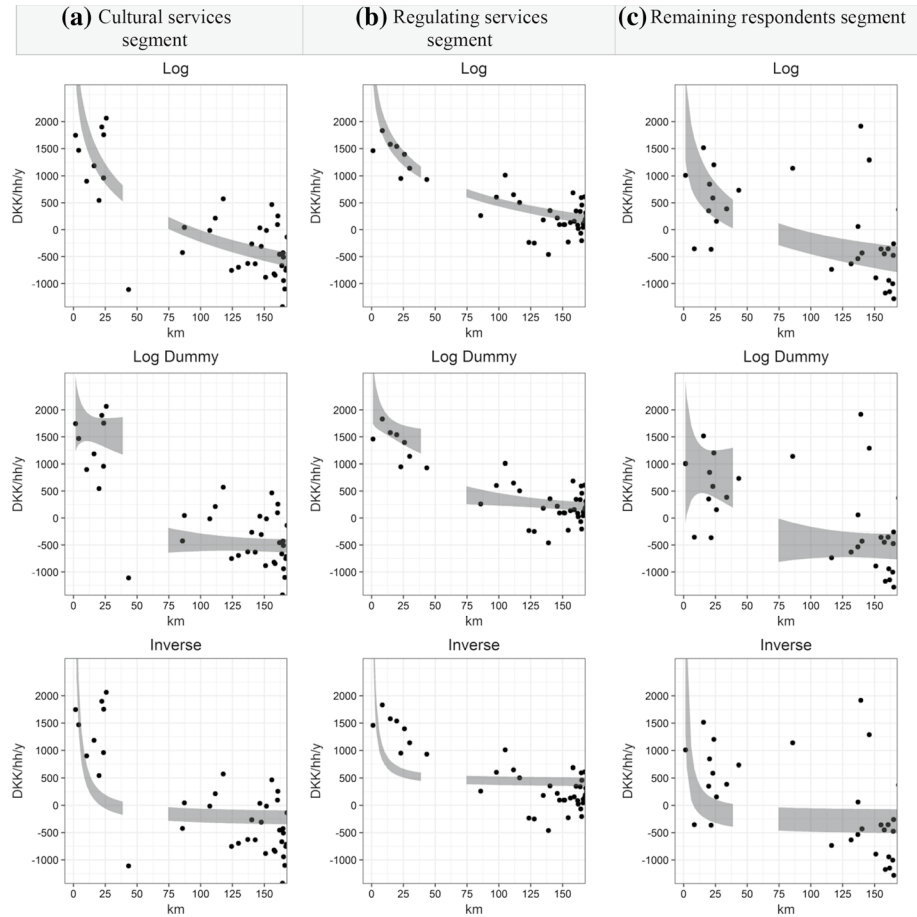


Fig. 4 Distance decay in WTP (Log, Log with dummy and Inverse specifications)

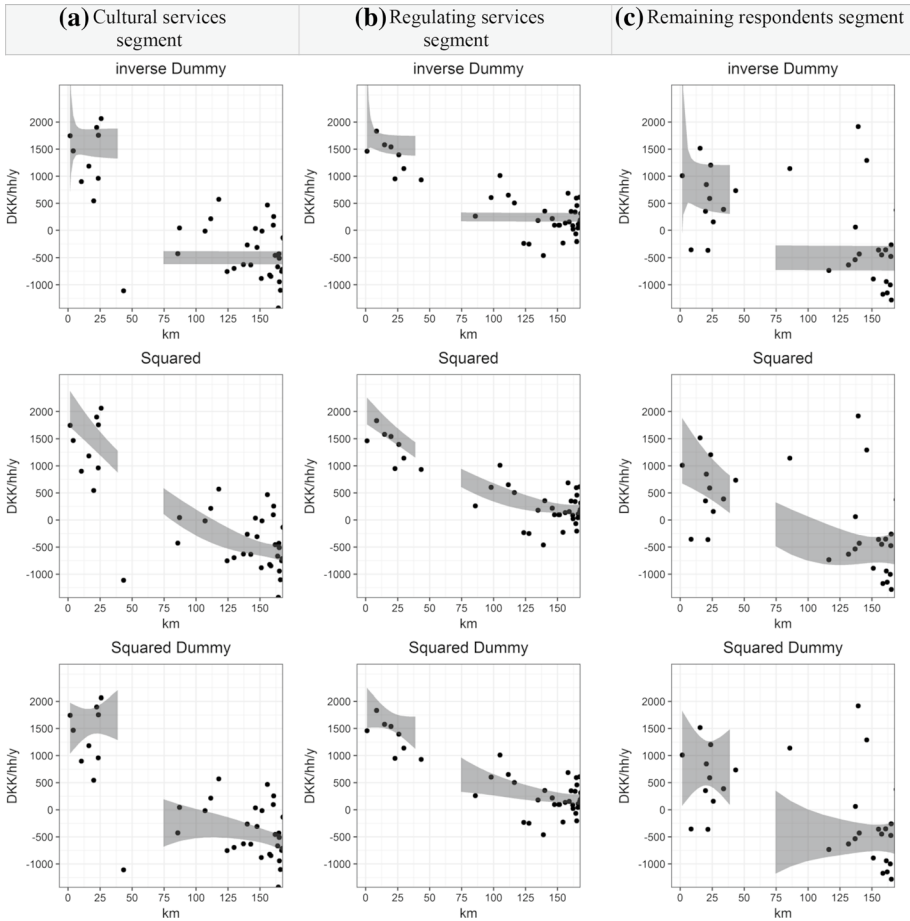


Fig. 5 Distance decay in WTP (Inverse with dummy, squared and squared with dummy specifications)

Appendix 3: Model Estimates and Graphical Illustrations of Estimated Distance Decay Relationships Assuming the Jump Discontinuity is not Known a Priori

See Tables 8, 9, 10 and Figs. 6, 7, 8.

Table 8 Distance decay models for cultural services segment

	GAM	Linear	Linear dummy	Log	Log dummy	Inverse	Inverse dummy	Squared	Squared dummy
Distance	***	-10 ^{***} (1)	-9 ^{***} (2)	-547 ^{***} (54)	-285 ^{**} (140)	5777 ^{***} (931)	1054 (1076)	-9 [*] (5)	5 (12)
Distance ²								0 (0.02)	-0.05 (0.05)
d_Zealand			-172 (334)		-683 ^{**} (339)		-1229 ^{***} (159)		-801 (632)
Constant	-94 [*] (52)	1127 ^{***} (124)	1126 ^{***} (124)	2391 ^{***} (253)	1747 ^{***} (407)	-233 ^{***} (60)	861 ^{***} (153)	1107 ^{***} (167)	875 ^{***} (248)
N	553	553	553	553	553	553	553	553	553
Adj,R ²	0.17	0.17	0.17	0.15	0.16	0.06	0.15	0.17	0.17
LL	-4719	-4718	-4719	-4725	-4724	-4752	-4725	-4719	-4719
UBRE	1,505,180	1,502,496	1,507,236	1,539,290	1,533,559	1,703,051	1,542,358	1,507,872	1,508,948

Standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9 Distance decay models for regulating services segment

	GAM	Linear	Linear dummy	Log	Log dummy	Inverse	Inverse dummy	Squared	Squared dummy
Distance	***	-6 ^{***} (1)	-6 ^{***} (2)	-343 ^{***} (40)	-263 ^{**} (103)	2688 ^{***} (566)	733 (628)	-6 [*] (3)	-9 (9)
Distance ²								0.00 (0.02)	0.01 (0.03)
d_Zealand			37 (239)		-201 (236)		-700 ^{***} (104)		175 (438)
Constant	499 ^{***} (36)	1242 ^{***} (90)	1242 ^{***} (90)	2082 ^{***} (188)	1873 ^{***} (309)	441 ^{***} (39)	1050 ^{***} (98)	1248 ^{***} (125)	1305 ^{***} (190)
N	1292	1292	1292	1292	1292	1292	1292	1292	1292
Adj.R ²	0.06	0.06	0.06	0.05	0.05	0.02	0.05	0.06	0.06
LL	-11,095	-11,093	-11,094	-11,097	-11,097	-11,121	-11,100	-11,094	-11,095
UBRE	1,681,931	1,676,964	1,679,536	1,686,123	1,687,786	1,751,239	1,694,550	1,679,559	1,681,959

Standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10 Distance decay models for segment covering remaining respondents

	GAM	Linear	Linear dummy	Log	Log dummy	Inverse	Inverse dummy	Squared	Squared dummy
Distance	***	-5*** (2)	-3 (4)	-277*** (99)	-119 (241)	2603* (1420)	926 (1596)	-7 (8)	-1 (20)
Distance ²								0.01 (0.04)	-0.01 (0.08)
d_Zealand			-199 (574)		-392 (547)		-567** (257)		-297 (1017)
Constant	-190** (96)	381* (217)	375* (218)	1052** (457)	645 (729)	-255** (103)	220 (238)	427 (301)	329 (452)
N	165	165	165	165	165	165	165	165	165
Adj,R ²	0.04	0.04	0.04	0.04	0.04	0.01	0.04	0.04	0.03
LL	-1411	-1410	-1411	-1410	-1411	-1412	-1411	-1411	-1412
UBRE	1,547,587	1,527,542	1,545,318	1,535,491	1,549,584	1,575,806	1,548,705	1,546,004	1,564,441

Standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

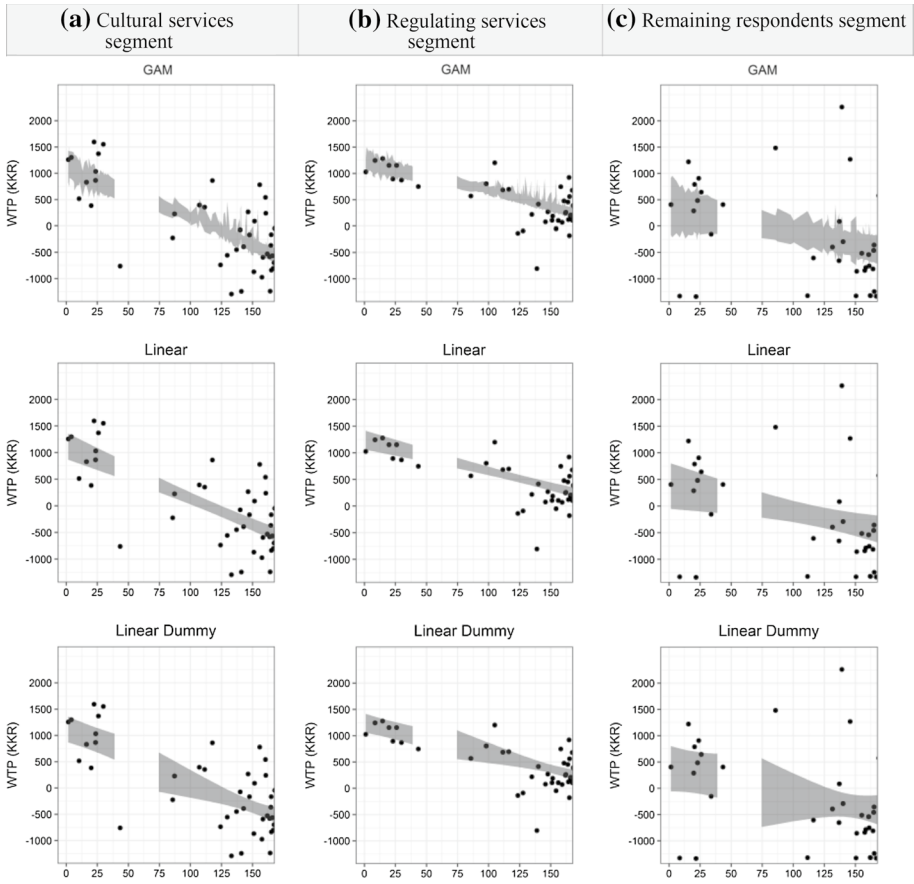


Fig. 6 Distance decay in WTP (GAM, linear and linear with dummy specifications)

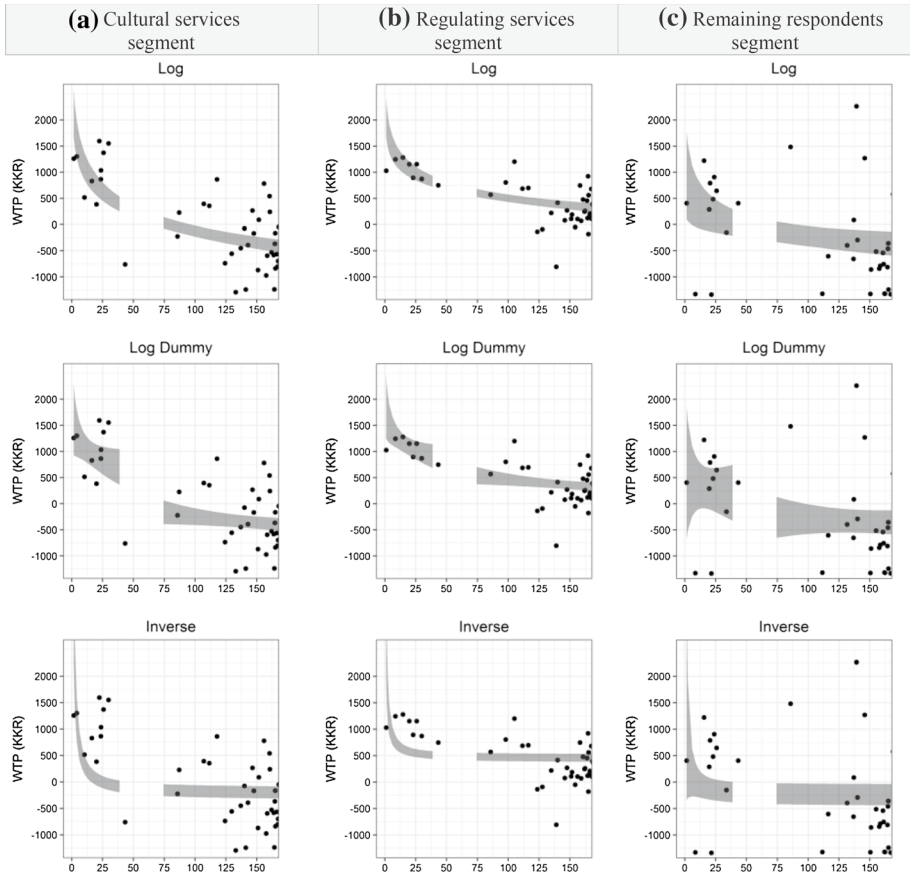


Fig. 7 Distance decay in WTP (Log, Log with dummy and inverse specifications)

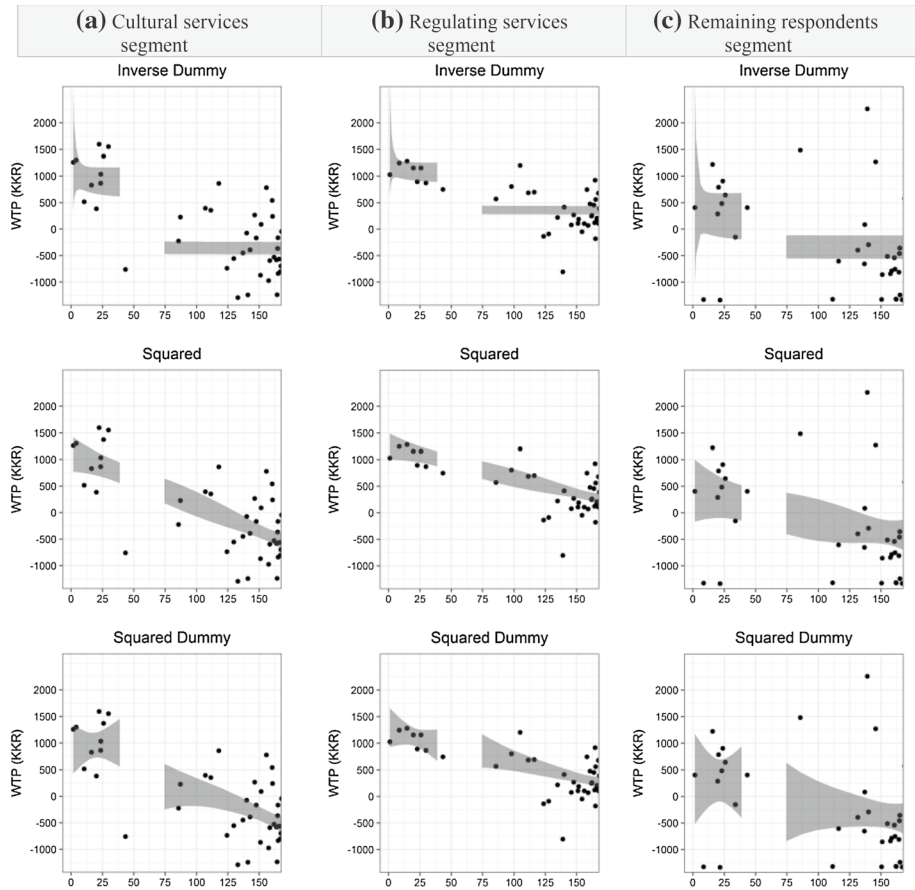


Fig. 8 Distance decay in WTP (inverse with dummy, squared and squared with dummy specifications)

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