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On the Validity and Reliability of coastal quality change estimates: Evidence from Norway

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Abstract: Coastal managers are faced with the challenge of managing sites to maintain or improve their quality. The quality of each coastal site is characterized by site attributes that visitors care about. Since coastal managers face financial constraints, it is useful to know which are the site attributes with the highest implicit value for visitors and thus determine the change in attributes that yields the most benefits. However, estimates of implicit value of site attributes should be both valid and reliable to be informative for coastal managers. If coastal sites present similar characteristics, the data can suffer from lack of variation that can lead to unreliable estimated implicit values. We first present our strategy relying on simulation that confirms that our estimates are unbiased, but only a subset of these is reliable. We then apply the discrete choice model to explain recreational beach site choice by using two alternative models with a view to increase precision of our estimates. We uncover preference heterogeneity by relying on observable group characteristics. We illustrate the policy-relevance of our approach by providing welfare estimates for three scenarios currently being considered by Norwegian beach managers.

JEL Codes: Q50

Keywords: site choice model; beach recreation; Norway; random utility model

1. Introduction

Managers of recreational sites are responsible for improving and maintaining the quality of sites over which they have jurisdiction towards enhancing visitors' experiences. To this end, they should consider increasing the quality of these sites if the benefits of their improvement exceed the costs of implementing those changes. However, the recreational benefits of changes in the quality of coastal sites are not evident. For recreational sites, no market prices exist and information predicting how visitation changes given policy scenarios is scarce, requiring economists to rely on non-market valuation methods to estimate benefits and costs. This is due to the public good nature of recreational sites, being non-excludable and non-rival. Our goal is to apply non-market valuation methods to estimate the implicit values of different attributes and identify which attributes have the greatest impact on recreationists' welfare. Managers of recreational sites can thus identify which changes in site attributes people care most about, which is especially useful if managers face restricted financial resources.

The use of the travel cost method (TCM) applied to recreation is an example of the valuation of non-market goods and services especially tailored to estimate recreation values. The TCM is a revealed preference method wherein the price to recreate at a site is the travel cost incurred to reach that site (Parsons, 2017). While the analysis of recreational choices has both a participation and a site choice component, we focus on site choice, wherein discrete choice models are often used. Analyzing site selection rather than participation frequency has some advantages: it allows for substitution across sites and we may estimate the implicit values of site attributes in a more straightforward manner (Parsons, 2017; Phaneuf and Requate, 2017).

However, a challenge arises when operationalizing a discrete choice model of site choice. That is, if lack of variation and high correlation of the explanatory variables (site attributes) are present in the data, the estimation of some model parameters is highly imprecise or, in extreme cases, not possible due to identification issues. While estimates can remain unbiased when ignoring lack of variation and high correlation, estimated implicit value of attributes may be unreliable and resulting policy implications are misleading.

Our data is characterized by high correlation and lack of variation in the attribute matrix. These phenomena are common when handling RP or observed data (Adamowicz et al., 1994; Ben-Akiva et al., 2002; Earnhart, 2002), especially if the environmental goods available are rather homogenous. Two strategies have been proposed to solve the problem of identification in RP data: either combining RP with SP data to break the multicollinearity (von Haefen and Phaneuf, 2008), or ensuring proper identification by using Murdock (2006)'s two-stage strategy. However, nor do we have access to SP data, nor variation in the data to obtain sufficiently precise estimations by the Murdock (2006)'s strategy. Instead, we use simulation to investigate the identification of the parameters of our model prior to estimation. We do this in four steps. In the first step, we define hypothetical population parameters based on a priori information. In the second step, we compute hypothetical utilities of all sites and for each respondent using parameter values defined in the first step, actual beach attributes and simulated idiosyncratic error terms. The highest utility of each respondent represents the hypothetical choice. In the third step, we use the hypothetical choices to estimate a choice model and save the estimated parameters. The steps 2 and 3 are repeated sufficiently high number of times and the saved estimations are used to obtain the empirical distributions of the estimators of the model parameters. In the last, fourth step the hypothetical population parameters from the first step are compared to the obtained empirical distributions. The above described simulation exercise can be used to analyze the effect of the functional form of the respondent utilities on the identification of the parameters and precision of their estimations. After both simulation and estimation, we show how we can improve precision of our estimates without compromising validity.

To the best of our knowledge, this is the first paper that tackles unbiasedness and precision in RP data by simulating data. The proposed solution to the identification problem expands the toolkit of practitioners that wish to investigate whether their welfare estimates are both valid and reliable.

Accounting for preference heterogeneity is also relevant in the context of recreational choices. We opt for controlling for observable preference heterogeneity through the introduction of interaction effects in the model.

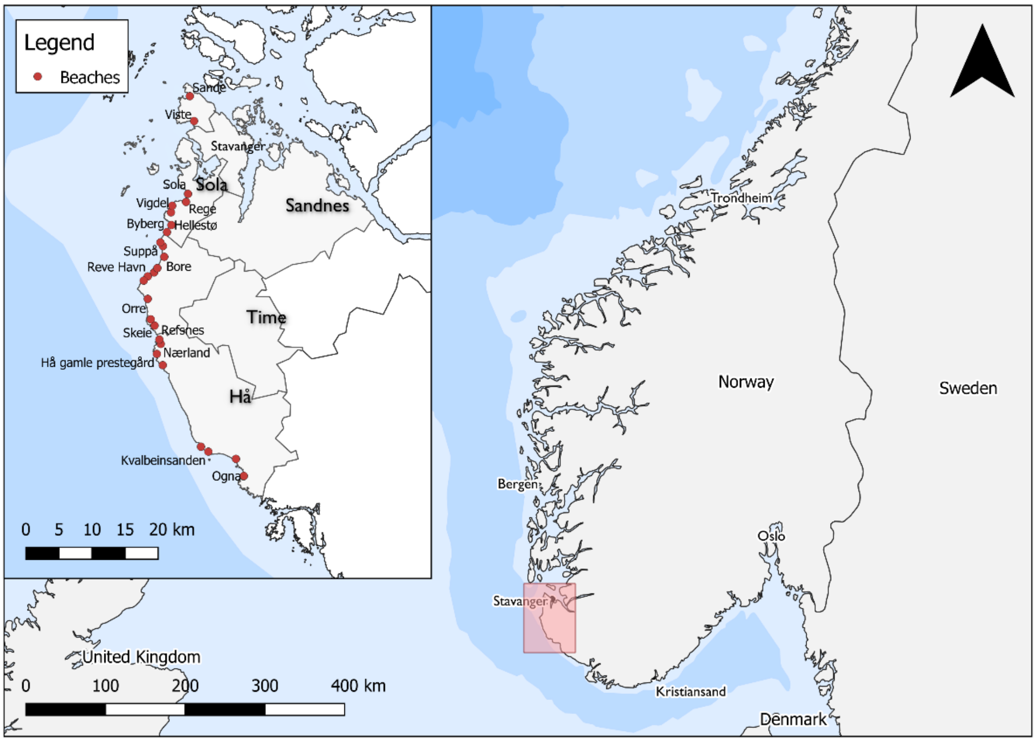
The remainder of this paper is structured as follows. Section 2 describes the survey design process and data. Section 3 describes the identification strategy. Section 4 presents the results. Section 5 presents welfare change measures from three scenarios currently being considered by Norwegian coastal managers. Section 6 concludes.

2. Data

Our case study pertains to the *Jæren* beaches in Norway. The *Jæren* beaches are located on the west-southern coast of Norway in the county of Rogaland and are some of the most visited natural attractions in the country with at least 600.000 visitors per year (Sveen, 2018). The vast majority of these visits are day trips, making beach recreation in *Jæren* a pertinent case for the application of the TCM. To the best of our knowledge, this is the first study to apply a site choice model to recreational choices in Norway.

Along the *Jæren* coast there are thirteen popular beaches and other less known sites (Sveen, 2018). These beaches are located in a 70-kilometer stretch from *Tungenes* in the North to *Ogna* in the South (see Figure 1). The area is classified as a nature conservation area since 1977 due to its geological, botanical, zoological and cultural heritage value. The beaches have white sand, dunes and many rare species and vegetation systems. The coast provides areas for birds to find shelter and nest.

Figure 1. Map of the study area: the Jæren coast and its beaches



To collect data on beach visitation, we conducted an off-site survey during October and November of 2018 using a web panel from a survey company (*Norstat*). Whereas most TCM data are collected on-site (e.g., Bin et al., 2007), we sampled residents in the Rogaland county of Norway and collected 982 responses, resulting in a response rate of 25.9%.

2.1. Survey Design

Survey design started in January 2017. Students carried out three pilot studies: one in Easter 2017 (Bui and Sæland, 2017) and two in Easter 2018 (Gilje, 2018; Kleppe and Jensen, 2018). Sampling for the pilot studies was done on-site at four beaches. We were able to identify the attributes visitors care most about, the activity engaged in by respondents, and obtain the first estimates of consumer surplus.

We based the design of the survey on nine previous state-of-the-art studies that resulted in a site choice model application (e.g. Bin et al., 2007; Bujosa et al., 2015; Chen, 2013; Hicks and Strand, 2000; Leggett et al., 2014; Lew and Larson, 2008; Matthews et al., 2018;

Parsons et al., 1999; Yeh et al., 2006). Three national environmental economics experts commented on the design of the survey, specifically to reduce recall bias. We consulted coastal managers, namely from *Jæren Friluftsråd* and *Fylkesmannen i Rogaland,* who helped expand the list of beach names, and identify coastal threats and relevant policy scenarios.

In order to gather data to design the questionnaire, we conducted one focus group in March 2018. The eight participants, who were employees at the university, were not informed about the topic of the discussion before the meeting. The focus group included a discussion concerning motivations for choosing a particular location, identification of the coastal threats, and ranking of beach attributes.

To test the survey, we conducted six personal interviews in September 2018. We first asked participants to fill out the survey without assistance. We then asked them some debriefing questions about general comprehension of the survey and various aspects related to their last visit (e.g., the relevance of overnight trips and identification of appropriate substitute sites).

2.2. Survey Data Description

Our dataset comprises 982 respondents who are residents of the Rogaland county in Norway. Nearly all respondents (98.3%) reported knowing or having heard of at least one of the beaches in *Jæren*. On average, respondents took 29 minutes to respond to the survey and a median time of 16 minutes.

To ensure that our sample is representative of the Rogaland population, we compare key statistics of the population with the sample means in Table 1. Respondents were randomly selected, which implies that every member of our population of interest (residents of the Rogaland county) has the same probability of being selected to answer the survey. Respondents were also not informed about the topic of the survey prior to answering it. We conclude that the sample is representative, as most sample means are not statistically different from the population means (see Table 1)[1]. Respondents were on average older and more educated than the population, as is common in Internet-based surveys (e.g., Lindhjem, 2011). We replace missing data on income with the population's mean income, adjusted for the number of household members.

Table 1. Comparison of Descriptive Statistics between Population of county residents and Respondent Sample (N = 965)

		Respondent Sample	**Population (county)**
Continuous Variables		**Mean**	**Mean**
Household Gross Income (NOK per year)		808 333	874 400
Household Size		2.56	2.32
Age		47.28	37.62
Dummy Variables		**Proportion**	**Proportion**
Education Attainment	Primary school	4.49%	25.70%
	High school	36.15%	39.20%
	Vocational or university education	59.36%	35.10%
Gender (% of women)		54.30%	49.20%

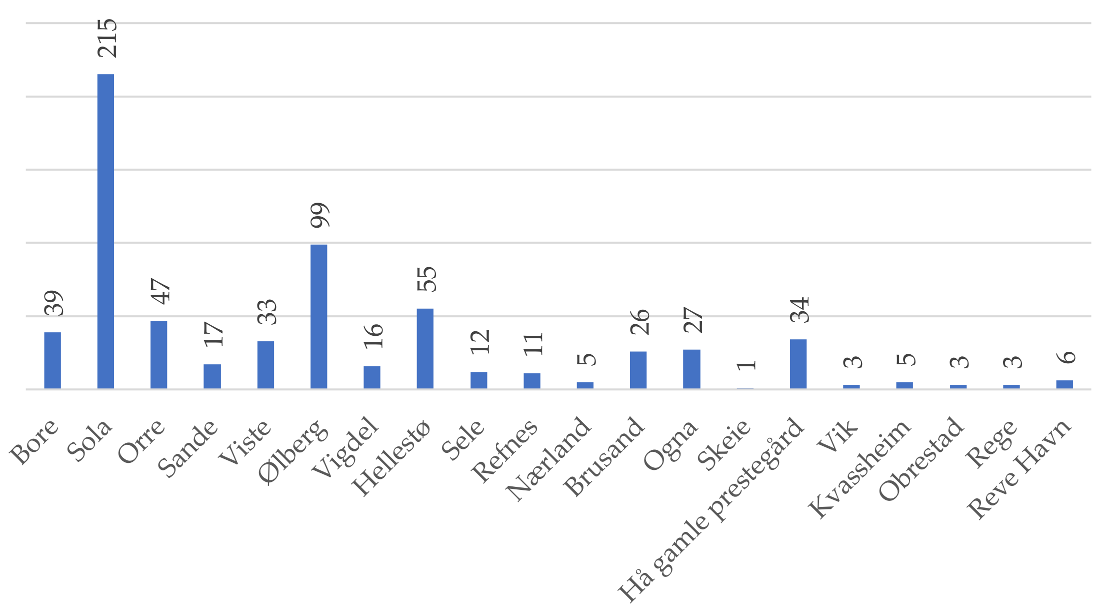
Source: SSB (Statistics Norway) for population means for the year 2016. As of 12/06/2019: 1 Euro = NOK 9.7710; 1 USD = NOK 8.6318 (Source: https://www.bloomberg.com/markets/currencies)

Our survey elicits both the respondent's general visitation pattern, and detailed information on the last beach visit during the summer season of 2018. Around 68% of the

[1] Although respondents are on average 10 years older than the population, this is because we excluded people under 18 years of age from answering the survey. When excluding people under 18 years of age, the average age is 47.94 according to Statistics Norway (SSB), which is in line with the sample mean (47.28).

sample reported having at least one visit to the Jæren beaches in the summer season of 2018. Therefore, the final sample size to analyze the choice of the last beach visited consists of 657 respondents. The thirteen main beaches represent 89.6% of the visitation. The most visited beaches are *Sola* (32.7%) and *Ølberg* (15.1%), followed by *Bore, Orre*, and *Hellestø* (see Figure 2). Norwegians use beaches differently from traditional beach users: the intention upon visiting for the majority of the respondents is to go on walks or to relax.

Figure 2. Distribution of last visited beach reported along the twenty Jæren beaches



The respondent's travel cost represents the various costs incurred to visit the beach. The calculation of the travel cost is conditional on the mode of transportation, which we elicited for each respondent. The majority of respondents traveled by diesel car (40%) and by petrol car (34%). The remainder traveled by electric car (7%), hybrid car (9%), bicycle (3.8%), public transportation (2.4%) and on foot (3.2%).

The travel cost C_{ij} to beach j of group i is given by:

$$C_{ij} = \left(p_d d_{ij} + f_i + 2p_j g_i + w_i t_{ij}\right) * \delta_i. \qquad (1)$$

where p_d denotes the per kilometer cost of travel, and d_{ij} the round-trip distance traveled in kilometers. Therefore, for groups traveling by car, $p_d d_{ij}$ is the roundtrip distance traveled times the money cost (in Norwegian kroner) per kilometer. We measure the distance traveled between the respondent's zip code and the beach's parking lot coordinates using the google maps API tool.

Groups traveling by diesel, petrol or hybrid cars also incur a toll fee, denoted by f, of 20 NOK. For groups traveling by bus or train, we multiply the ticket price, denoted by p_j (35 and 70 NOK, respectively) by the group size g_i irrespective of the distance traveled.

The round-trip travel time spent (in hours) t_{ij} was calculated using the google maps API tool, and it is conditional on the group's mode of transportation. If groups are free to choose the number of hours worked at a given wage rate, then the opportunity cost of time, w_i, simplifies to the group's wage rate (Freeman et al., 2014). w_i is assumed to be one third of the group's net hourly wage rate, given an average of 1950 hours of work per year. We adjust for multiple-purpose trips following the method proposed by Yeh et al. (2006), and thus weigh the travel cost variable with the term δ_i, which denotes the percentage of the travel reported to have been spent in that beach.

We collected data on fifteen beach attributes: number of parking spaces, dummy for area being protected for birds, water quality index, beach length and width, presence of rocks, dunes, marina, trash boxes, bike paths nearby and camping possibilities, number of toilets, public access points to beach and food amenities (bars, restaurants and kiosks), and congestion.[2] These attributes are summarized in Table 2. Many of the attributes we collected are common in the site choice modeling literature, such as beach length and parking (Bujosa et al., 2015; Hilger, 2006; Lew and Larson, 2008; Massey and Parsons, 2007), beach width (Bin et al., 2007), level of congestion (Cushman et al., 2004), and water quality (Hicks and

[2] We have more attributes than the average in site choice models applied to beach recreation (average of 9.69 attributes in 39 studies). The number of attributes in past studies ranges from 2 (Chen and Lupi, 2013; Hicks and Strand, 2000; Whitehead et al., 2008a) to 30 (Pendleton et al., 2012)

Strand, 2000). The problem related with the matrix describing beach attributes is the focus of the next Section.

Table 2. Beach Attributes' Description (name, description, data source, average, standard deviation, minimum and maximum attribute level for all 20 sites)

Name of Variable	**Description**	**Source**	**Mean**	**Standard Deviation**	**Min**	**Max**
Parking Spaces	Number of public parking spaces available	Coastal Managers (Jæren Friluftsråd)	123.45	107.08	0	360
Congestion	Average number of daily visits (i.e. density) divided by beach length and width (in meters)	Own calculation	0.03	0.14	0	0.58
Water Quality	Water Quality score (from 1 to 5)	Vann-nett portal	3.8	0.4	3	4
Bird Protected	Bird Protection area	*Fylkesmannen i Rogaland*	0.35	0.48	0	1
Length	Length of the beach (in meters)	Spatial data (Google maps satellite images)	805.45	836.91	0	2810
Width	Width of the beach (in meters)	Spatial data (Google maps satellite images)	32.07	17.62	0	68
Rocks	Dummy: 1 if the beach has rocks or cobblestones; 0 if only white sand	Spatial data (Google maps satellite images)	0.4	0.49	0	1
Dunes	Dummy: 1 if the beach has dunes; 0 otherwise	Coastal Managers (Fylkesmannen i Rogaland)	0.6	0.49	0	1
Toilets	Number of toilets	Coastal Managers (Jæren Friluftsråd)	1.7	1.38	0	4
Food Amenities	Number of restaurants, bars and kiosks nearby	Coastal Managers (Jæren Friluftsråd) & Visitor Reviews (Trip Advisor)	0.75	0.89	0	3

Bike Path	Dummy: 1 if the beach has bike path nearby; 0 if otherwise	Spatial data (Google maps satellite images)	0.15	0.36	0	1
Marina	Dummy: 1 if the beach has a marina or boating dock nearby; 0 otherwise	Spatial data (Google maps satellite images)	0.35	0.48	0	1
Camping	Dummy: 1 if the beach has camping facilities; 0 otherwise	Spatial data (Google maps satellite images)	0.2	0.4	0	1
Trash boxes	Dummy: 1 if the beach has Trash boxes; 0 otherwise	Coastal Managers (Jæren Friluftsråd)	0.5	0.5	0	1
Public Access	Number of main public access points	Spatial data (Google maps satellite images)	1.45	0.67	1	3

3. Identification Strategy

We use discrete choice modeling to analyze recreational data (e.g., English et al., 2018). Our theoretical framework is the Random Utility Model (RUM), which is laid down in Haab and McConnell (2002), Parsons (2017), Phaneuf and Requate (2017), and Freeman et al. (2014). The underlying idea behind the RUM framework is that a visitor should choose to visit the site that gives the highest utility when facing a choice set of recreational sites.

We analyze a single choice occasion (i.e., last visited beach by each respondent) using the conditional logit model. Utility is a function of travel cost C_{ji} and K beach attributes q_{jk}, which are the same across respondents but differ for each beach (e.g., length of the beach, water quality, or presence of dunes). Utility is expected to increase with desirable beach attributes (e.g., water quality), and decrease with undesirable beach attributes (e.g., unclean beaches). Each of the j beaches corresponds to a bundle of beach attributes (q_{jk}), as well as a cost of travel C_{ij} associated with getting there. The basic setting of the RUM in our case is:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = ASC_j + \beta_M C_{ji} + \sum_{k=1}^{K} \beta_{q_k} q_{jk} + \varepsilon_{ij}, \quad (2)$$

where the individual's (i) utility U_{ij} of visiting beach j is decomposed into an unobservable error term ε_{ij} and an observable component V_{ij} (indirect utility) that depends linearly on an alternative specific constant, travel cost and beach attributes.

The parameters β_M and β_{q_k} represent the marginal utility of money and the k^{th} beach quality, respectively. We can calculate the marginal Willingness to Pay (WTP) for attribute q_k as:

$$WTP_k = -\frac{\beta_{q_k}}{\beta_M}. \qquad (3)$$

Linearity in parameters in the functional form of the indirect utility function (2) is a relatively standard approach in the discrete choice modelling literature. This functional form also needs to ensure proper identification of the parameters of interest, which pertains to the unambiguous determination of the coefficients of the model (Lancsar and Louviere, 2008). The identification of the parameters is closely related to the variation in the matrix of attributes (right hand side matrix in equation (2)).

While in SP data the variation of the attribute data is generated by the experimental design, in RP studies data on attributes are often collected objectively by researchers based on direct observation or existing data (Adamowicz et al., 1997). As a result, many attributes with RP data either do not have enough variation (e.g., an attribute taking the same value across beaches) or suffer from high collinearity (e.g., highly or perfectly correlation between two or more attributes). Our data are a prime example of this, as it suffers from both lack of variation and high collinearity. For example, lack of variation is present in the water quality variable: although the scale ranges from 1 to 5 (very bad to very good quality, respectively), the observed water quality along the study site only takes the value 3 (moderate) or 4 (good quality). High multicollinearity is also present in our data. For example, the correlation coefficient between the attribute levels for camping and food amenities is relatively high (0.72). Multicollinearity and lack of variation can complicate the precise estimation of parameters of interest. In such a case, including all attributes to explain site choice can result in estimated coefficients having counter-intuitive signs and/or being statistically (in)significant. This is because these data issues cause flat regions in the log-likelihood function that is maximized in the estimation process of our discrete choice model. The numerical optimization methods applied in the maximum likelihood estimation process can easily end up in those flat regions that do not generally represent the global maximum of the maximized function. Alternatively, if the maximized solution happens to be the global maximum, a possible flatness of the function can lead to high standard errors and imprecise estimation. Welfare analysis conducted with such estimated parameters can easily yield seemingly statistically insignificant welfare measures, when in fact the scenarios considered increase or decrease welfare.

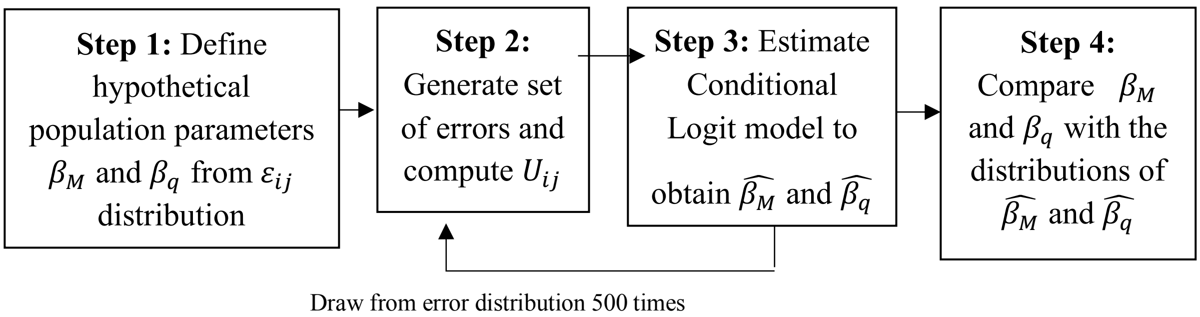
Problems with RP data is one of the main motivations of combining RP and SP data (von Haefen and Phaneuf, 2008; Whitehead et al., 2008b). Some studies, such as Adamowicz et al. (1994), Ben-Akiva et al. (2002), and Earnhart (2002), combine data sources to reduce the collinearity present in the attribute levels and thus allow for the strong identification of attribute coefficients.

If SP data is not available, Murdock (2006) proposes a two-stage strategy to ensure unbiased parameters of attributes with RP data. In the first stage, a discrete choice model is estimated given travel costs, any interaction of individual and attributes characteristics, and a full set of alternative specific constants. These constants should absorb and isolate the impact of time-invariant site-specific attributes (including those unobserved by the analyst). In a second stage, the estimates of these constants of the first stage become the dependent variable in an ordinary least squares regression and the observed site attributes are the explanatory variables. The number of observations in this second-stage is equal to the number of available sites. Some site choice model applications already apply this strategy (e.g., Timmins and Murdock, 2007). However, this strategy may not yield reliable estimates if the number of observations in the second stage is low.

Another strategy to reduce collinearity is to use factor or principal component analysis. Both these methods establish a correlational structure among the observed variables by creating latent variables called “factors” or “loadings” that can explain beach choice instead of beach attributes (Basilevsky, 1994). However, factor analysis and principal component analysis are not viable solutions in our case because the ultimate goal of our analysis is to inform coastal managers about the relative value of attributes, rather than the relative value of latent constructs which coastal managers cannot change.

Instead, we use simulation to investigate the reliability and validity of β_{q_k} and β_M estimates prior to estimation. In the remainder of this section, we describe the simulation strategy employed. The simulation approach is summarized in Figure 3.

Figure 3 – Summary of identification strategy (Steps 1 through 4) for each specification



In Step 1, we define hypothetical population values of parameters β_{q_k} and β_M based on preliminary estimates. The assumed values of the parameters are assumed to be the values from employing Murdock’s strategy (reported in the first column of Table 3). If a particular specification does not include a specific attribute, we set the assumed value of its parameter to zero.

Table 3. Assumed Parameters and Results from Pre-testing for Beach Attributes

		Importance of attributes

Name of Variable	Assumed Parameter Value	Focus Group (relative importance)	Pilot Studies Surveys (score from 1 to 5)
Travel Cost	-0.008	Very important	3.18
Parking Spaces	0.003	Very important	4.17
Congestion	-4.477	Somewhat important	2.88
Water Quality	-0.774	Somewhat important	
Bird Protected	0.282	Somewhat important	3.67 (Pristine nature and wildlife)
Rocks	-1.476	Not Important	
Dunes	-0.125	Somewhat important	
Length	-0.0001	Somewhat important	
Width	0.002	Somewhat important	
Toilets	0.038	Very important	2.63
Food Amenities	0.541	Somewhat important	1.51
Bike Path	1.020	Not Important	
Marina	0.686	Not Important	
Camping	0.194	Not Important	
Trash boxes	-0.053		
Public Access	0.393		

In the second step, we compute the hypothetical utilities U_{ij} of all sites j and for each respondent i according to:

$$U_{ij} = -\beta_M C_{ij} + \boldsymbol{\beta}'_q \boldsymbol{q}_j + \varepsilon_{ij}, \tag{5}$$

where $\boldsymbol{q}_j$ is a vector representing various combinations of beach attributes, $\boldsymbol{\beta}_q$ is the corresponding vector of parameters and ε_{ij} is the idiosyncratic error assumed to be identically and independently Gumbel distributed. The hypothetical choice of each individual is set by the highest utility.

These hypothetical choices are used in the third step to estimate a conditional logit model and the estimated parameters are saved for posterior analysis. The steps 2 and 3 are repeated 500 times and estimations of each iteration are used to obtain the empirical distributions of the model parameters. We check if the assumed hypothetical parameter value falls inside of the 2.5th and 97.5th percentiles of the empirical distribution. If it does, we conclude that the specification yields unbiased, hence valid, parameter estimates. We also analyze the precision, i.e. reliability, of the estimated coefficients by analyzing the spread of the distributions of the model parameters.

Including all 15 attributes and 19 alternative specific constants to explain beach choice is not possible due to the existence of perfect multicollinearity. We look, therefore for a combination of attributes that allows for correct identification and precise estimation of all model parameters. First, we omit the alternative specific constants from the utility function. While it may seem a restrictive assumption, estimating the value of beach attributes is our primary focus. Second, we keep specifications that include four of the attributes found to be relevant in the pre-testing phase of the survey. The results of the focus group and pilot surveys were consistent in terms of which attributes were the most relevant for visitors (see Table 3). These are distance from home, clean beaches, parking and toilet facilities, and pristine nature (Kleppe and Jensen, 2018). Hence, we include number of parking spaces, toilet facilities, whether the beach is bird protected and presence of dunes (as an indication of pristine nature) to explain beach choice. These two restrictions narrow down the number of possible specifications to 2047 (i.e. all possible combinations of remaining 11 attributes). In Section 4.1, we illustrate the usefulness of our simulation approach by investigating the precision and unbiasedness of parameter estimates in different alternative specifications.

We also simulate whether the variation of the attribute levels in our sample is sufficient to identify parameters in more complex models such as mixed logit or latent class model that allow modeling of unobserved preference heterogeneity. The results indicate that the variation of the attribute levels in our dataset is not sufficient to retrieve the additional parameters in these more complex models. That is why we opt for adding flexibility to our conditional logit model by interacting the attribute coefficients with the observed group characteristics.

4. Results

4.1. Simulation Results

Before estimation, we used the above described simulation strategy to analyze the precision and unbiasedness of the parameters of interest. The aim is to understand the usefulness of the parameters to be estimated for coastal managers, which should be both valid and reliable.

We first use our simulation strategy to infer on validity of the parameters. We implement the four steps described in Figure 3 to find out whether different specifications of the indirect utility function yield unbiased estimates. If the data generation process is correctly specified, we conclude that including all attributes to explain site choice yields unbiased parameters. An example how this is done visually is shown in Figure 4a and 4b below. These histograms are the outcome of our simulation for the specification with all 15 attributes plus travel cost. These present the empirical distribution of the estimator of a specific parameter based on the 500 hypothetical utilities. We then compare the distributions with the assumed parameter value represented by a vertical line. If the assumed parameter value falls within the 0.025 and 0.975 percentiles of the estimated parameters' distributions, we conclude that the model is able to retrieve the parameter values from the underlying data generation process. As can be easily seen in Figures 4a and 4b this is the case for all attributes. Moreover. we check whether the specification with all 15 attributes is able to retrieve the assumed parameter values with different underlying data generation processes, that is different specifications of the utility function that includes less attributes.[3] Since it does, we conclude that using all 15 attributes to explain site choice provides unbiased, hence valid parameter estimates, despite data suffering from high collinearity and lack of variation.[4]

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[3] We would like to note that this specification may still suffer from omitted variable bias if we fail to account for additional attribute that are relevant to explain site choice.

[4] As pointed out by a referee, the simulation outcome is sensitive to the assumed hypothetical population parameters (see Step 1 in Figure 3). It is important to highlight that the set of assumed true values for the

The problem is that the precision of the estimated parameters is very low. As seen in Figures 4a and 4b, the empirical distributions of the estimated parameters have a large spread. For eleven out of fifteen attributes, such as parking spaces and being bird protected, the empirical distributions are very wide and include zero between the 0.025 and 0.975 percentiles that indicate that the attributes can easily be non-significant in the estimation based on real data. Hence, for our sample size, there is not enough variation in the data to provide a precise estimate. This implies that estimated parameters and respective welfare changes are likely to be statistically insignificant. On the other hand, coastal managers might have tacit knowledge indicating that true values are different from zero, thus decreasing credibility of the research.

parameters used in our simulation was based on values obtained from the Murdock's approach, while yields unbiased estimates. We conduct a robustness check by choosing different combinations of hypothetical population parameters and run additional simulations. More specifically we change these values to plausible ones given the estimates obtained from Murdock’s approach. It is true that the simulation exercise will be always incomplete as there is an infinite number of combinations of the assumed true values. Nonetheless, our additional simulations based on variation of these values offer a relatively high degree of robustness of our results.

Figure 4a. Assumed parameter value (vertical line) and empirical distribution of the 16 parameters for specification including all 15 attributes

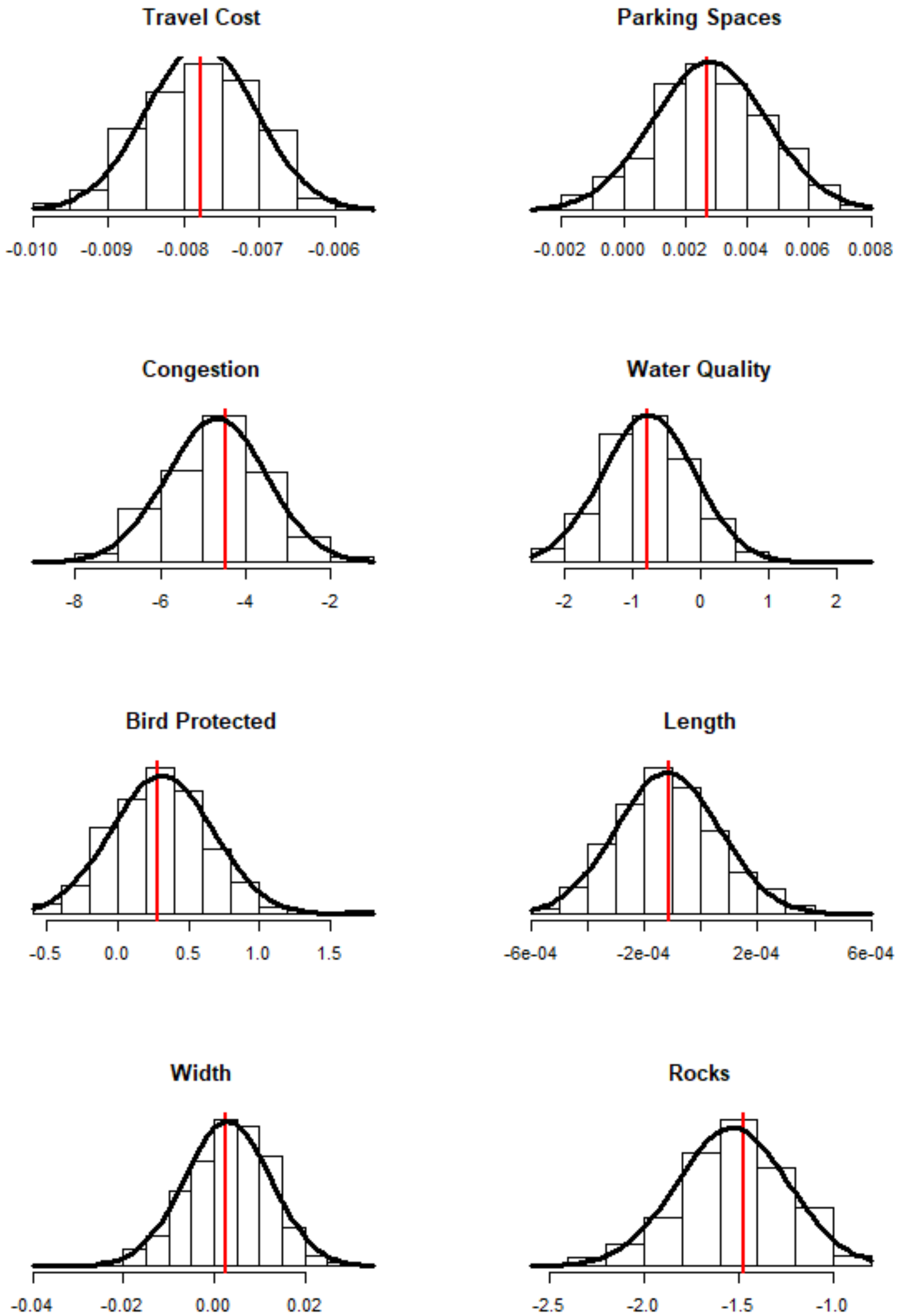
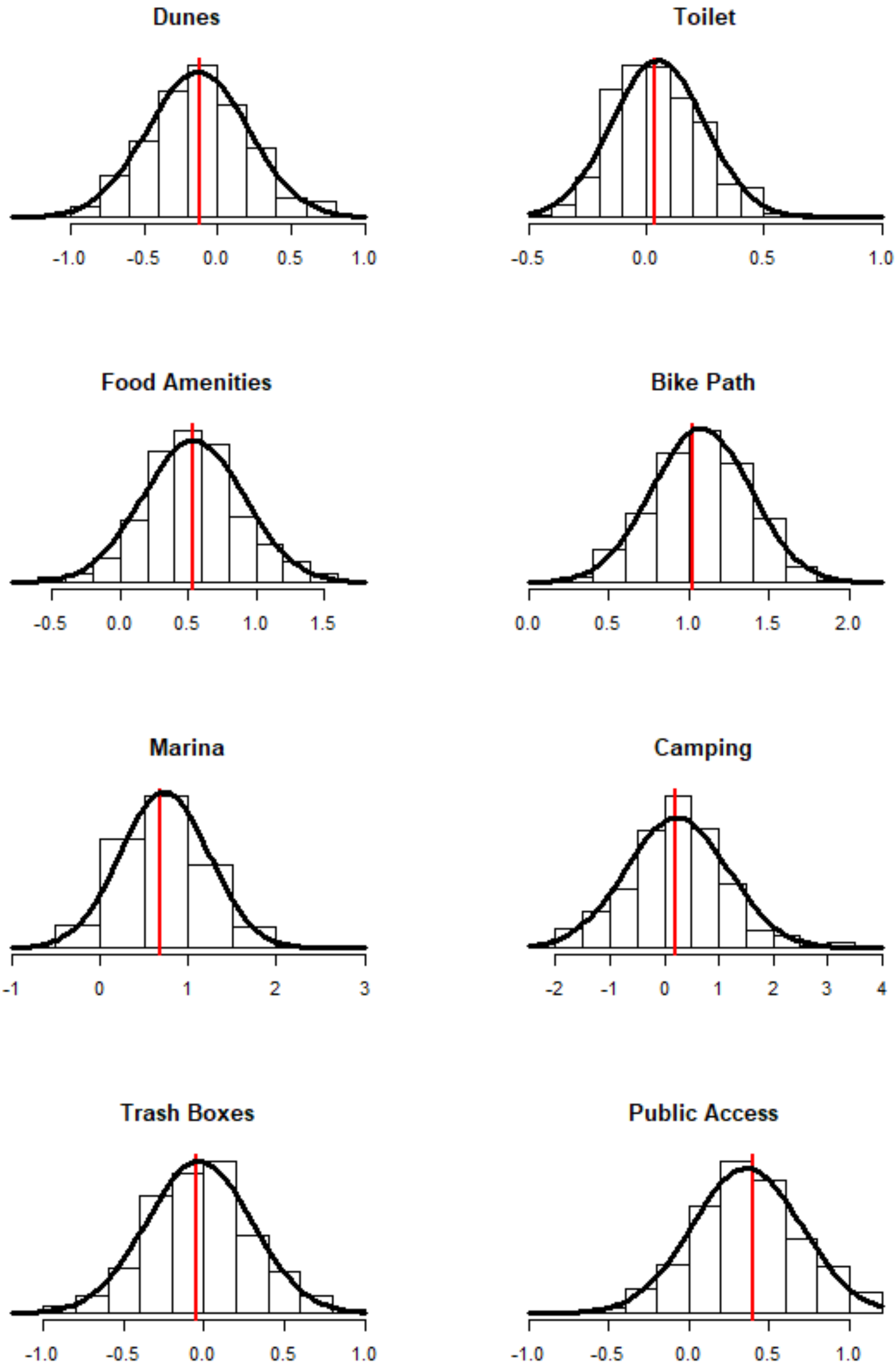


Figure 4b. Assumed parameter value (vertical line) and empirical distribution of the 16 parameters for specification including all 15 attributes



We may improve precision by choosing a specification that omits some of the attributes that are highly correlated. However, omitting attributes might lead to omitted variable bias, which puts the validity of the results into question. Again, we use the simulation exercise to identify a specification that does not suffer from omitted variable bias even if the underlying data generation process includes the omitted variables, but that decreases the spread of the empirical distributions of model parameters. We set the assumed parameter values to be those shown in Table 3, irrespective of whether the parameter will be accounted for or not in the specification. We find that only 38 specifications out of 2047 possible combinations do not suffer from omitted variable bias from omitting some of these 15 attributes. To improve precision, we want to omit as many attributes as possible while preserving unbiasedness, so we choose the specification with 10 attributes. This specification includes parking spaces, congestion, water quality, bird protected, rocks, dunes, toilets, food amenities, bike path and marina. The results of the simulation exercise are shown in Figures 5a and 5b. In black, we show the distribution of estimated parameters of the 15-attribute specification and in the dashed line that of the 10-attribute specification. For the 10-attribute specification, the assumed parameter values (the vertical line) fall within the 2.5th and 97.5th percentiles of the empirical distributions. Across attributes, the distributions are narrower for the 10-attribute specification, rather than the 15-atttribute specification but the bias due to the omission of some attributes is negligible. This is what we mean by gains in precision by choosing a subset of attributes. This is the model we use for comparison purposes in Section 4.2.

Figure 5a. Assumed parameter value (vertical line) and empirical distribution of the 16 parameters for specification including all 15 attributes (in black) and specification with 10 attributes (in grey dashed line)

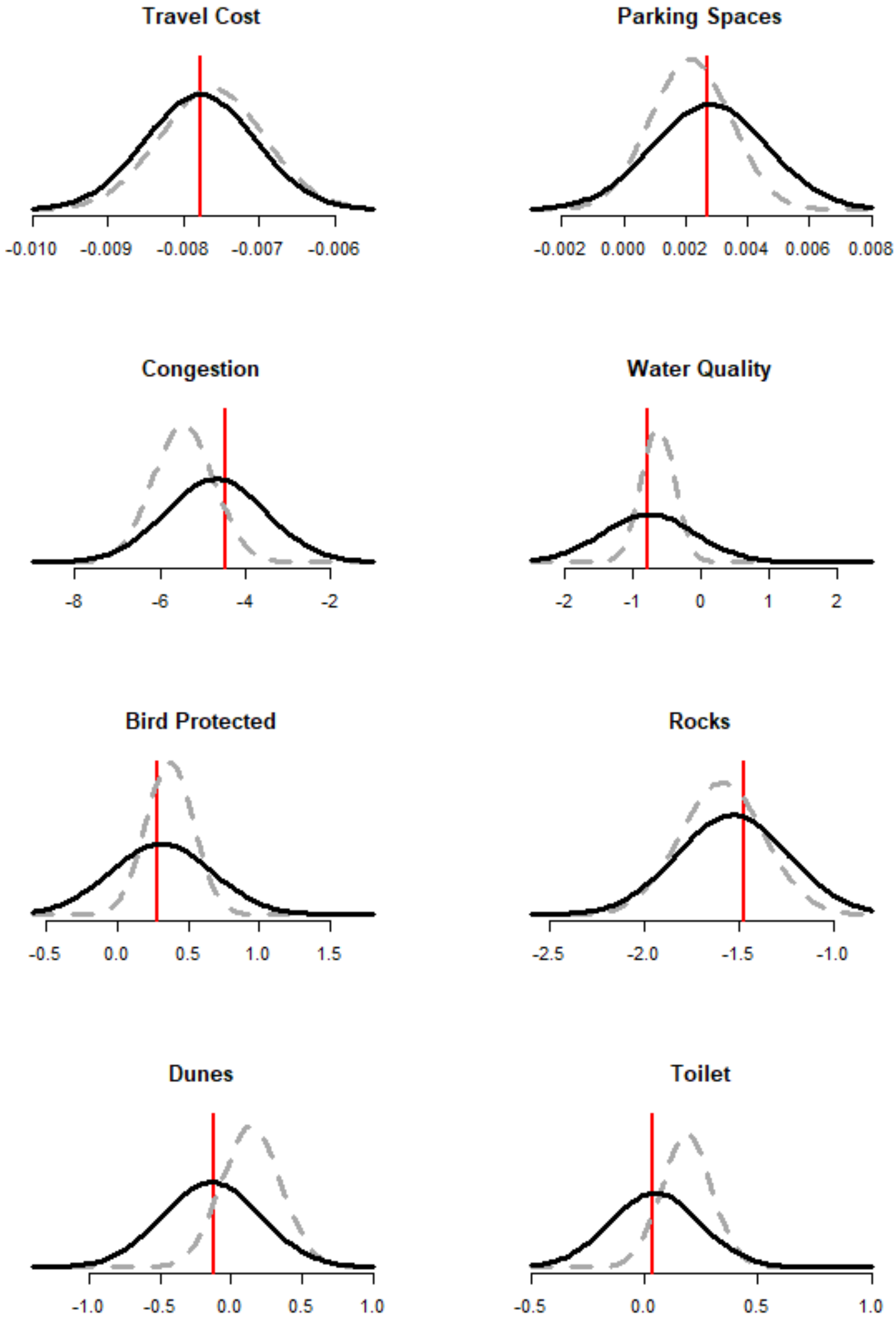
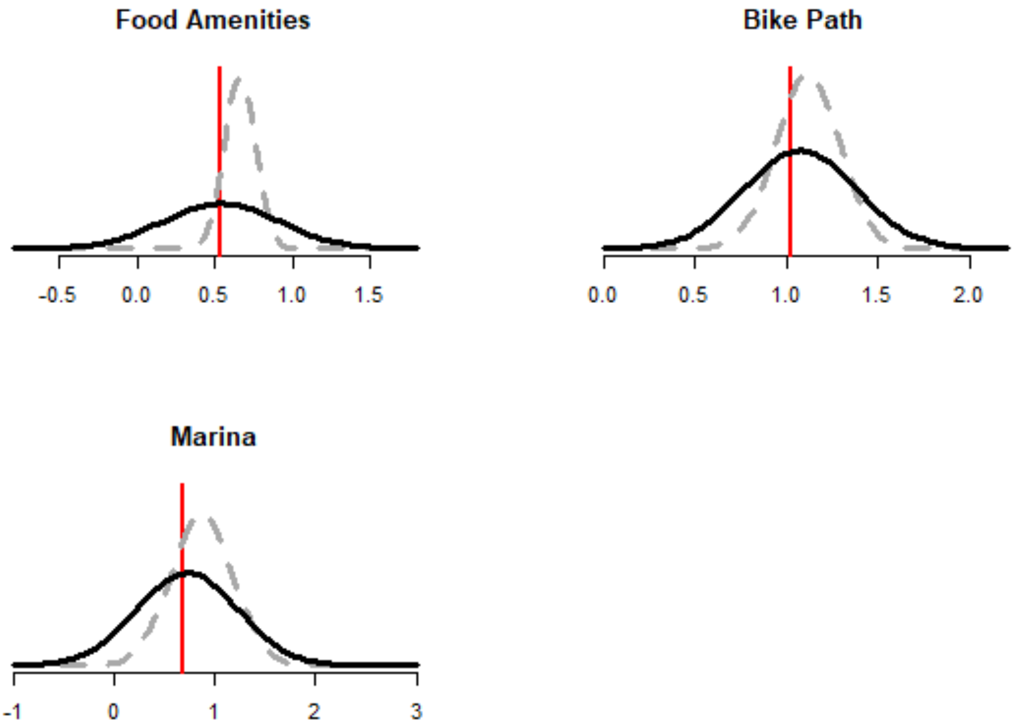


Figure 5b. Assumed parameter value (vertical line) and empirical distribution of the 16 parameters for specification including all 15 attributes (in black) and specification with 10 attributes (grey dashed line)



4.2. Estimation Results

We analyze the choice of the last visited beach in the 2018 summer season along the *Jæren* coast. These choices are conditional on individual and site-specific travel costs, and site-specific attributes. We have twenty beaches along *Jæren* that respondents reported as their last visited beach.

We first report in Table 4 the estimated coefficients of three distinct models. The first model we report is Murdock (2006)'s strategy, which should yield unbiased estimates. We then report a specification wherein we include all 15 attributes as explanatory variables. This is the specification chosen if the researcher wants to include all available data (attributes) but does not address high multicollinearity and lack of variation in the matrix of attributes. We finally report estimated coefficients using the specification we identify using simulation in

Section 3 (with 10 attributes), which minimizes omitted variable bia but improves precision of the estimates.

Table 4. Estimation Results for the Conditional Logit Model with all attributes, Murdock's 2-stage strategy and Conditional Logit model with 10 attributes

	Murdock's Strategy	Conditional Logit Model with all (15) attributes	Conditional Logit Model with 10 attributes based on our identification strategy
Travel Cost	-0.008*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)
Parking Spaces	0.003 (0.004)	0.005** (0.002)	0.004** (0.001)
Congestion	-4.477 (3.466)	-5.702*** (1.171)	-4.720*** (0.690)
Water Quality	-0.774 (1.431)	-0.324 (0.637)	-0.714** (0.253)
Bird Protected	0.282 (0.769)	0.744* (0.343)	0.487** (0.150)
Length	-0.0001 (0.001)	-0.0001 (0.0002)	
Width	0.002 (0.021)	0.006 (0.010)	
Rocks	-1.476* (0.670)	-1.660*** (0.264)	-1.600*** (0.19)
Dunes	-0.125 (0.921)	-0.319 (0.356)	0.129 (0.186)
Toilets	0.038 (0.434)	-0.071 (0.183)	-0.136 (0.105)
Food Amenities	0.541 (0.747)	0.098 (0.331)	0.490*** (0.092)
Bike Path	1.020 (1.242)	2.202*** (0.306)	1.645*** (0.174)
Marina	0.686 (0.957)	0.545 (0.470)	0.355 (0.284)
Camping	0.194 (2.049)	1.140 (0.825)	
Trash Boxes	-0.053 (1.929)	0.313 (0.290)	
Public Access	0.393 (1.015)	-0.290 (0.326)	
Number of Attributes	15	15	10

Number of observations	657 (first-stage) 20 (second-stage)	657	657
Log-likelihood	-1418 (first-stage)	-1434	-1437
AIC	2875 (first-stage)	2900	2897
BIC	2965 (first-stage)	2972	2946

Note: *** denotes statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Murdock (2006)'s strategy yields unbiased estimates, but only the coefficients associated with travel cost and rocks are statistically significant at the 5% significance level. All other coefficients have implausible high standard errors.

In the second column, we report the parameter estimates for the 15-attribute model. These parameters are unbiased if there are not any remaining attributes that drive site choice and are correlated with any of the 15-attributes (e.g., clean beaches). The point estimates of this model (and of the 10-attribute model) are relatively close to the estimates obtained by Murdock's strategy. The precision of these estimates improves slightly, with the coefficients associated with parking spaces, bird protected and bike path becoming statistically significant.

In the third column, we report the parameter estimates for the 10-attribute model. There are additional gains in precision, with the coefficients associated with food amenities and water quality becoming statistically significant at the 5% level, and bird protected being statistically significant at the 1% level. Our 10-attribute model also exhibits better fit when comparing the AIC and BIC than the 15-attribute model. In conclusion, the estimation results confirm the simulation result, to wit, precision improves when using the 10-attribute specification.

The estimates obtained conform to result of previous studies. Across all models, the travel cost variable is negative and statistically significant, thus exhibiting negative price sensitivity (Bishop and Boyle, 2019). Like previous studies (Bestard, 2014; Lew and Larson, 2008; Parsons and Stefanova, 2009), we find that parking (i.e., number of parking spaces) is considered an amenity and hence increases the probability of visitation. Our 10-attribute model indicates that good water quality is a disamenity, but this is likely to be due to lack of variation, as water quality is generally perceived by previous studies to be an amenity (Hilger and Hanemann, 2006). Our results indicate that areas protected for birds are perceived to be amenities, which conforms to previous findings that protected areas are amenities to visitors (Du Preez et al., 2011). The opposite is true for the presence of rocks: our results conform to previous findings by Lew and Larson (2005) in San Diego beaches that the presence of rocks decreases the probability of visitation.

We are aware of the limitations associated with including congestion as an explanatory variable. The well-known challenge of including congestion is endogeneity: the same unobserved factors that drive the site choice of the individual also influence congestion at each site (Hindsley et al., 2007). Most authors account for the endogenous nature of congestion using an instrumental variables approach (e.g., Boxall et al., 2005; Timmins and Murdock, 2007) in the two-stage model proposed by Murdock (2006). We include congestion without the use of instrumental variables as the collected data do not allow for more complex model estimation and loss of efficiency, generally related to instrumental variable approach. As expected, congestion is perceived as a disamenity for visitors.

Using our 15- and 10-attribute models, we focus on preference heterogeneity by accounting for observed characteristics of the individuals. Common variables that can explain preference heterogeneity include gender, age, group size, number of children in the group, and income. However, the beach choice is the result of a group based decision process, rather than an individual decision. Group characteristics are more likely to explain better beach choice rather than individual characteristics. Indeed, when interacting beach attributes with several individual characteristics (i.e., age, gender, membership to an environmental or touristic organization, and perceived knowledge about coastal fauna and flora), we do find that group characteristics explain beach choice better than individual characteristics (see

Appendix 1 for measures of fit of various models). Kaoru (1995) also find evidence that group composition influences recreational decisions.

Given data availability, we use group size to disentangle the observed preference heterogeneity. The median group had two people, while the average group consisted of 3.13 visitors. Additional variables to uncover preference heterogeneity include the activity engaged in by the group (e.g., sunbathing, running, fishing, walking, and relaxing) or number of children. However, the fit of these specifications is inferior to those of the specifications using group size (see Appendix 1).

We estimate two conditional logit models with group size interactions (results are reported in Table 5). The above-mentioned conclusions regarding improvements in precision persist: standard errors using the 10-attribute model are lower than the 15-attribute model. As predicted, travel cost has a negative impact on utility, and hence on the probability of visitation.[5] At the mean, less congestion, absence of rocks and bike path are welfare-enhancing and significant. In the 10-attribute model, bird protection status and food amenity facilities are also welfare-enhancing and significant. Adding the interaction effects improves the fit of the model when compared with the model omitting any interactions (BIC decreases from 2946 to 2932; see Appendix 1 for details).

Table 5. Estimation Results for the Conditional Logit Model with group size interactions

	15-attribute Conditional Logit Model	10-attribute Conditional Logit Model

[5] We do sensitivity analysis on the travel cost variable by: 1) not adjusting for multiple-purpose trips (Yeh et al., 2006) hence assuming that δ is one for all respondents; 2) using the self-reported departure coordinates to calculate distances and times instead of the postal code; 3) using a different percentage (50%) of the wage rate as the opportunity cost of time. While the coefficients of all attributes (except travel cost) remain unchanged, the fit of the models deteriorate in all of the sensitivity analyzes. Therefore, we choose to keep the adjustment for multiple purpose trips as proposed by Yeh et al. (2006), the postal codes as the departure coordinates, and 33% of the wage rate as the opportunity cost of time.

Dep. Var.: Beach Choice	Mean Effect	Interaction effects with group size	Mean Effect	Interaction effects with group size
Travel Cost	-0.011*** (0.001)	0.0002*** (0.00002)	-0.011*** (0.001)	0.0001*** (0.00001)
Parking Spaces	0.005 (0.004)	0.0002 (0.001)	0.001 (0.002)	0.001 (0.0004)
Congestion	-5.479*** (1.324)	-0.136 (0.346)	-4.687*** (0.853)	-0.163 (0.231)
Water Quality	-0.539 (1.184)	0.107 (0.430)	-0.392 (0.321)	-0.107 (0.067)
Bird Protected	0.909 (0.621)	-0.029 (0.226)	1.036*** (0.242)	-0.177** (0.066)
Length	0.0001 (0.0003)	0.0001 (0.0001)		
Width	0.024 (0.018)	-0.007 (0.006)		
Rocks	-1.309*** (0.414)	-0.122 (0.122)	-1.497*** (0.270)	-0.040 (0.066)
Dunes	-0.678 (0.636)	0.109 (0.225)	0.212 (0.286)	-0.052 (0.082)
Toilets	-0.048 (0.357)	0.011 (0.128)	0.055 (0.164)	-0.052 (0.047)
Food Amenities	0.435 (0.611)	-0.122 (0.212)	0.589*** (0.136)	-0.013 (0.036)
Bike Path	2.442*** (0.508)	-0.137 (0.154)	1.920*** (0.284)	-0.132 (0.080)
Marina	0.440 (0.944)	0.047 (0.350)	0.740 (0.419)	-0.138 (0.105)
Camping	0.200 (1.576)	0.411 (0.567)		
Trash Boxes	0.361 (0.434)	-0.040 (0.125)		
Public Access	-0.658 (0.481)	0.191 (0.127)		
Number of observations	657		657	
Log-likelihood	-1386.7		-1394.8	
AIC	2838		2834	
BIC	2981		2932	

Note: *** denotes statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Preferences differ given group size in what concerns the travel costs and bird protected status. Preference heterogeneity regarding the travel cost variable is fairly intuitive: the larger the group, the more the group shares the costs of travel, and thus they are less sensitive to the travel cost variable. This result conforms to the findings in Kaoru (1995). Larger groups also value less bird protected beaches (in the 10-attribute model).

Given the preference heterogeneity regarding some beach attributes, the marginal WTP for each attribute should vary across groups' size. Three of the most common group compositions in our sample are one, two and four-person groups. To highlight the differences, we estimate marginal WTP for each attribute for 1-person and a 4-person group both for the 15- and 10- attribute model.

Table 6 reports the estimated marginal WTPs per visit. The standard errors of the WTPs are computed by the delta method.

Table 6. Marginal WTP (in NOK and per group) for beach attributes in Jæren beaches

	15-attribute Conditional logit model		10-attribute Conditional logit model	
	1-person	4-person group	1-person	4-person group
Parking Spaces	0.43 (0.24)	0.38 (0.24)	0.14 (0.13)	0.36** (0.13)
Congestion	-498.35*** (113.85)	-557.26*** (113.85)	-435.65*** (72.09)	-499.60*** (72.09)
Water Quality	-38.36 (75.86)	-10.28 (75.86)	-44.90 (25.87)	-76.93** (25.87)
Bird Protected	78.10 (40.52)	73.41 (40.52)	77.21*** (18.05)	30.84 (18.05)
Length	0.003 (0.02)	-0.02 (0.02)		
Width	1.52 (1.16)	-0.41 (1.16)		
Rocks	-127.08*** (30.96)	-166.48*** (30.96)	-138.14*** (23.51)	-155.29*** (23.51)
Dunes	-50.51 (41.65)	-22.50 (41.65)	14.35 (20.83)	0.21 (20.83)

Toilets	-3.27 (22.76)	-0.23 (22.76)	0.26 (11.79)	-14.29 (11.79)
Food Amenities	27.79 (39.84)	-4.98 (39.84)	51.76*** (10.24)	50.20*** (10.24)
Bike Path	204.64*** (40.86)	175.43*** (40.86)	160.61*** (25.15)	130.30*** (25.15)
Marina	43.17 (59.24)	57.95 (59.24)	54.07 (31.74)	17.55 (31.74)
Camping	204.64 (100.96)	170.63 (100.96)		
Trash Boxes	28.53 (31.49)	18.70 (31.49)		
Public Access	-41.40 (35.96)	9.94 (35.96)		

Note: *** denotes statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level. As of 12/06/2019: 1 Euro = NOK 9.7710; 1 USD = NOK 8.6318 (Source: https://www.bloomberg.com/markets/currencies)

The same conclusions regarding precision are made when analyzing WTP estimates. The WTP is statistically insignificant for many attributes in the 15-attribute model. WTP estimates are statistically significant only for the case of congestion, presence of rocks and bike path. For example, one person is willing to pay 127.08 NOK to visit a beach without rocks. WTP are not statistically different for 1-person or a 4-person group. The 10-attribute model reveals that some groups have a statistically significant WTP to obtain a marginal increase in additional attributes: parking spaces, bird protected and food amenities. This model also highlights WTP differences across different group sizes in what concerns bird protected areas and parking. While one person is willing to pay 77 NOK to visit a bird protected beach but not willing to pay to have access to more parking spaces, a 4-person group is not willing to pay for the bird protection status but is willing to pay 0.36 NOK per visit for an additional parking space.

5. Policy Implications

We illustrate the change in welfare from three beach management scenarios. First, we consider the improvement of parking and toilet facilities. These were undertaken in 2018 in one of the most popular beaches, but during the time of surveying, these were not open to the public (Personal Communication, *Jæren Friluftsråd*). Further improvements are expected in another beach by 2022 (Schibevaag, 2016). We estimate of the benefits of improving facilities, consisting of 154 additional parking spaces in *Bore* and 20 additional parking spaces in *Brusand* beach, as well as adding an extra toilet in both *Bore* and *Brusand* beaches (Schibevaag, 2016). We expect a slight welfare gain in this scenario.

Second, the *Jæren* area is under several threats, including the wear-and-tear of beach dunes. This threat is especially relevant, not only for visitors but for the coastal environment. In six of the 20 beach sites, it is recommended to avoid walking on dunes since these are damaged (Fylkesmannen i Rogaland, 2018). The second scenario simulates the change in CV in case these six sites were to lose their dunes. We expect a welfare loss.

Third, available public transportation to and from the *Jæren* beaches is of poor quality. One coastal manager (*Fylkesmannen i Rogaland)* is currently considering the creation of a free bus route during the summer season from the two main cities (Stavanger and Sandnes). We simulate the welfare change from such a bus route to the five most visited beaches. We assume that visitors change from their elicited mode of transportation to this new bus route only if their group's travel cost is lower by choosing this bus route.[6] Hence, this change is

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[6] One referee pointed out that groups might have strong preferences towards the mode of transportation. For example, we expect that larger groups with more children would still not opt for using a free bus due to the convenience of travelling by car even if their travel costs are reduced. Hence, the assumption of groups changing their mode of transportation may not hold for some specific groups. In such a case, the number of people that would change mode of transportation would be overstated and the resulting welfare estimates of introduction of a free bus would be biased upwards. However, we do find that smaller groups with less children would use the free bus using the travel cost reduction assumption. We find that the average group size is smaller (albeit not statistically different) for the groups that take the free bus (2.5 people), rather than the groups that do not

through decreased travel costs for some of the visitors. We expect a welfare gain from this scenario.

Table 7 presents the mean and median CV given the three scenarios. To compute these CV estimates, we use the 10-attribute model with group size interactions. Estimates for the annual flow of benefits were obtained by assuming a lower bound number of annual visitors to *Jæren* of 600 000 (Sveen, 2018) and the mean group size from our sample of 3.12. This results in an estimate of 192 307 groups of visitors per year in the region.

Table 7. Compensating Variation in NOK (per group and per visit) for three policy scenarios

Mean CV in NOK (per group and per visit)	***Mean***	***Median***	***Median Annual Flow of Benefits***
Scenario 1: Increase in number of facilities (i.e., toilets and parking spaces) in two beaches (*Bore* and *Brusand*)	+2.73	+63.87	525 thousand NOK
Scenario 2: Loss of dunes in six beaches where dunes are currently damaged	-4.66	+34.70	-896 thousand NOK
Scenario 3: New bus route from main nearby cities to the five most popular beaches	+0.64	+10.02	123 thousand NOK

As expected, Scenarios 1 and 3 yield median welfare gains for visitors of 2.73 NOK and 0.64 NOK per group and per visit, respectively.[7] The loss of beach dunes in Scenario 2 generates a welfare loss for visitors at the mean (4.66 NOK per group and per visit), but not

take it (3.3. people). Likewise, the groups that change for the free bus have on average less children (0.34) than the groups that do not take the free bus (0.74 children). Therefore, we recognize the potential bias in the estimated welfare gain, but the resulting group composition gives credibility to the robustness of the assumption.

[7] The number of groups that would change from their elicited mode of transportation to the new bus route is simulated to be 144 out of the 657 responses. For these 144 groups, the travel cost variable decreases, hence the welfare gain in this scenario. While we would also expect that the number of total visits would increase given a new bus route, this model only predicts changes across visitation sites and is not able to predict changes in the number of visits. To this end, a repeated site choice model or a count model would be more appropriate.

at the median. Recreational value changes per year amount to -896 thousand to 525 million NOK across different scenarios.

6. Conclusions

The quality of coastal areas may change over time, namely due to pressure from human activities. Coastal managers may intervene by improving facilities or restricting access to sites. These interventions change the recreationist's probability of visiting each site, and it is useful for coastal managers to know how recreational values change when introducing new measures. The application of a site choice model allows us to estimate welfare changes in the face of different scenarios and willingness to pay (WTP) for coastal attributes.

However, to be useful for coastal managers, WTP estimates should be both reliable and valid. Ensuring the validity of estimates means these should be unbiased, while reliability concerns improving precision, i.e. minimizing the variation of the error term rather than its bias. If a WTP for a given attribute has an implausibly high standard error, changes in the underlying attribute will appear to yield statistically insignificant, hence unreliable, changes in welfare.

The underlying cause of a study's unreliability may be the data itself, namely, due to high collinearity and lack of variation. We propose using simulation to investigate identification issues prior to estimation and find to a functional form for the utility function that reduces the multicollinearity in the data by avoiding highly correlated explanatory variables while avoiding omitted variable bias. The proposed solution to the identification problem expands the toolkit of practitioners that wish to explain observed choices among similar goods with few alternatives (e.g., less than 30).

We apply our model to recreational choices in cold-water beaches on the southwestern coast of Norway. Our study is the first site choice model applied to Norway, and the third beach study-site in Europe wherein a site choice model is applied. We first illustrate the gains in terms of precision by comparing alternative ways of modelling site choice. We then estimate a conditional logit model by accounting for interactions between beach attributes and group size. We conclude that we may improve precision of our coastal attribute parameters by omitting some of the highly correlated variables, as long as we can minimize omitted variable bias from doing so.

We find that visitors care most about shorter distances (i.e., lower travel cost), less congestion, bird protection status, absence of rocks, food amenities and bike paths. When estimating WTP for attributes, we find that different groups have distinct preferences. Smaller groups prefer more pristine beaches (i.e., with bird protection status) and larger groups prefer more parking spaces. Changes in quantity or quality of these attributes will impact the welfare of groups differently.

We analyze three scenarios involving changes in beach quality: improvements in parking and toilet facilities in two beaches, dune deterioration and creation of a new bus route. The first and third scenarios involve an improvement in beach quality and a decrease in travel costs, respectively, and thus are welfare-enhancing. On the other hand, the loss of sand dunes results in a loss in welfare, highlighting the critical role of dunes for the experience of these visitors. We also show that the annual flow of recreational benefits is substantial, i.e. in the order of 100 to 800 thousands of Norwegian kroner per year. Managers of recreational sites should take into consideration these intrinsic values when improving and maintaining the quality of coastal sites.

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APPENDICES

Appendix 1 – Measures of Fit (AIC, BIC, AIC3 and CAIC) of 10-attribute Conditional Logit models with Interactions

	Interactions Considered	AIC	BIC	AIC3	CAIC
	None	2897	2946	2908	2957
Group Characteristics	*Group Size*	2834	2932	2856	2954
	Number of Children	2883	2982	2905	3004
	Group Size & Number of Children	2809	2958	2842	2991
	Purpose of Trip	2905	3152	2960	3207
Individual Characteristics	*Age of Respondent*	2888	2987	2910	3009
	Membership in Tourist Association	2899	2997	2921	3019
	Membership in Environmental Association	2910	3008	2932	3030
	Knowledge of local fauna and flora	2866	2965	2888	2987