Attribute non-attendance in environmental discrete choice experiments: The impact of including an employment attribute

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Abstract: This paper utilizes data from a split-sample discrete choice experiment to investigate the impact of including an employment attribute on stated preferences for protecting the coastal zone of Arctic Norway. The econometric analysis investigates how its inclusion affects attention to other choice experiment dimensions, and how welfare measures vary between the two sub-samples and across models that control for attribute non-attendance versus models that do not. We find that the employment attribute has a relatively high attendance rate and that its inclusion does not appear to decrease attention to other attributes of interest. The impact of the added attribute on the part-worth estimates for environmental attributes is mixed. However, similar to prior research, we find that controlling for attribute non-attendance tends to yield lower welfare estimates. Lastly, our analysis indicates somewhat higher attention to the cost attribute than many previous studies.

Key words: Stated preferences; discrete choice experiments; employment effects; attribute non-attendance; coastal ecosystem services.

JEL Codes: C25, H41, Q5, Q51, Q52

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INTRODUCTION

Discrete choice experiment (DCE) researchers face many difficult design decisions in developing their instruments (e.g., Louviere, Hensher, and Swait 2000; Hensher, Rose, and Greene 2005a; Johnston et al. 2017). Two central considerations of DCE design are *simplicity* and *saliency*. The former, simplicity, refers to making choice tasks cognitively manageable by limiting the number of alternatives, attributes, and the information content of these dimensions. In contrast, *saliency* refers to the identification and inclusion of all relevant choice aspects in the design.

A key challenge is that pursuit of saliency, through the examination of previous research and elicitation of input from experts and focus group, often leads one to identify too many attributes, which would imply excessively complex information processing and choice tasks for would-be respondents. Inevitably, the DCE designer is forced to balance the desire for completeness and realism against the need for parsimony and intelligibility (Louviere, Hensher, and Swait 2000; Hensher, Rose, and Greene 2005a; Johnston et al. 2017). Compounding the difficulty of this design trade-off is the fact that attributes important to some respondents may not be relevant for others due to differences in preferences. Respondents are also different in regard to their interest in and familiarity with the valuation context, and, relatedly, their willingness and ability to process relatively complex choice set information (Louviere, Hensher, and Swait 2000; Hensher 2006a).

The empirical manifestation of a data phenomenon called *attribute non-attendance (AN-A)* is directly linked to the design considerations of simplicity and saliency and respondent heterogeneity. In general, AN-A refers to choice contexts wherein the decision-making agent ignores, cancels out, or fails to pay attention to one or several aspects of the decision-process

(Hensher 2006b). For example, if a DCE is too complex, respondents may invoke various heuristics for processing information and making choices, including that of ignoring one or several attributes in one or several of the choice menus presented to them. Similarly, if the DCE is over-simplified, that is, lacking important choice aspects, it could be deemed unrealistic or inconsequential (Johnston et al. 2017). Respondents may then choose to put less effort into their preference expressions, also potentially leading to the empirical manifestation of AN-A. In both cases, extreme response patterns could transpire, including the selection of status quo or the cheapest alternative on every choice occasion, or choices made at random. While it is not common to find high presence of such extreme cases, an emerging AN-A literature has established that non-trivial shares of DCE participants tend to ignore one or several attributes (e.g., Scarpa et al. 2012; Hensher, Collins, and Greene 2013; Weller et al. 2014; Thiene, Scarpa, and Louviere 2015; Caputo et al. 2018).

Related to the issues of DCE design and AN-A is the issue of whether market impacts such as employment effects should be included in studies that seek to identify people's willingness to pay (WTP) for environmental goods. To illustrate, consider a DCE about preference for coastal zone management plans with important implications for the protection of various *non-market* ecosystem services. Should measures of market impacts be included in the design or not? It turns out that this is an unresolved and only marginally addressed question in the environmental valuation literature (e.g., Blamey et. al. 2000; Bergmann, Colombo, and Hanley 2008; Longo, Markandya, and Petrucci 2008). If market impacts are included, one might avoid confounding effects that could bias the estimated importance of environmental attributes (Blamey et al. 2000). On the other hand, including additional choice dimensions increases complexity and could, arguably, lead to double-counting in cost-benefit analysis (Diamond and Hausman 1994). A sampling of the most recent DCE studies from a selection of environmental economics journals reveals a mixed set of design approaches, sparse conceptual discussions, and no experimental explorations of this issue. Furthermore, very few of the surveyed articles include AN-A estimations.

The main contribution of our paper is to combine research on AN-A with investigation of the implications of including an employment attribute (job creation/losses) in the DCE design. We utilize a unique dataset from a valuation survey with split-sample design, with an employment attribute included in the DCE given to half the respondents. While some previous studies have explored the implications of choice complexity or differing design dimensions (e.g., Hensher 2006a, Hensher 2006b; Weller et al. 2014), ours is the first study to investigate the implications of including an employment attribute with a split-sample design.

The analysis focuses on the sensitivity of estimated WTP for environmental attributes to AN-A and the inclusion of the employment attribute. Specifically, we seek to answer four research questions: 1) How large is the share of respondents attending to the employment attribute when it is included? 2) How does inclusion of the employment attribute affect AN-A for the other attributes? 3) How do WTP estimates for environmental attributes compare across the two sub-samples? 4) How do WTP estimates compare between models that incorporate AN-A relative to models that do not?

The empirical context of the paper is coastal zone management in Arctic Norway. The dataset comes from a DCE survey designed to study the local population's preferences for regulating coastal activities and commercial development (Aanesen et al. 2018). The specific attributes included in the full DCE design were 1) industry impacts on landscape views, 2) catch rates in recreational fishing, 3) beach litter, 4) jobs creation/losses, and 5) change in annual tax payments. Approximately half the respondents received choice cards without the employment attribute. For both sub-samples, we estimate panel mixed logit models with multivariate normally distributed non-cost parameters. We explore AN-A through the flexible latent class, mixed logit model proposed by Hess et al. (2013).

LITERATURE BACKGROUND

We first give brief literature overviews on attribute non-attendance and the role of market attributes in DCE research. Then we summarize a sample of recent DCE articles from four environmental economics journals with respect to whether these two topics are explored.

Attribute Non-Attendance in discrete choice experiments

Research interests in the AN-A phenomenon emerged from the works by Swait (2001), Cantillo and Ortúzar (2005), Hensher, Rose, and Greene (2005b), Hensher (2006b), and, Hess and Rose (2007), to mention a few of the earlier contributions. Initially, AN-A research relied on self-reported attribute attendance information (e.g., Puckett and Hensher 2008; Carlsson, Kataria, and Lampi 2010; Rose et al. 2012; Scarpa, Thiene, and Hensher 2010). Then the research proceeded to develop statistical inference approaches to identifying AN-A prevalence (e.g., Hess and Hensher 2010; Campbell, Hensher, and Scarpa 2011). From there, the literature has gone in several related directions, including to the comparison of results from stated versus inferred approaches (e.g., Carlsson, Kataria, and Lampi 2010; Kragt, 2013; Scarpa et al. 2012; Weller et al. 2014; Caputo et al. 2018), developing flexible and increasingly sophisticated inference methods (e.g., Hensher, Collins, and Greene 2013; Weller et al. 2014), and attempting to uncover the reasons behind the AN-A phenomenon (e.g., Alemu et al. 2013; Weller et al. 2014). Throughout, one central focus point has been welfare estimates, that is, how WTP for specific attributes or attribute bundles is affected by whether or not AN-A is accounted for in the analysis (e.g., Hensher, Rose, and Greene 2005b; Campbell, Hensher, and Scarpa 2011; Scarpa et al. 2012; Hensher, Collins, and Greene 2013; Weller et al. 2014; Thiene, Scarpa, and Louviere 2015; Caputo et al. 2018).

Employment effects in discrete choice experiments

The main argument for including market impacts, such as employment effects, is *saliency*. That is, inclusion would lead to a more complete and realistic design. A possible side-effect of exclusion is that respondents infer market implications themselves, which, in turn, could lead to confounding effects and bias in WTP estimates of environmental attributes (Blamey et al. 2000). As example, suppose one attribute in a DCE for coastal zone management is number of endangered coastal bird and plant species, and that the researcher is interested in people's WTP for biodiversity conservation. In the absence of an employment control, some respondents may infer that management scenarios with a higher number of protected species (that is, fewer endangered species) is automatically associated with fewer jobs. This could then lead to an under-estimate of WTP for biodiversity conservation. Blamey et al. (2000) argue that omitting or downplaying development effects and providing unbalanced information in the DCE survey could result in blurry valuation contexts.

An additional argument for including market impacts, specifically job creation or losses, is that it can be argued that "employment" is a public good with non-market benefits that would not be reflected in the market information. For example, high employment rate may be one of several dimensions of a thriving community. Therefore, it is argued, people may have genuine preferences for job-creation regardless of whether own employment opportunities are affected or not (Morrison, Bennett, and Blamey 1999; Othman, Bennett, and Blamey 2004). Furthermore, people may value the option of having more employment opportunities available to themselves and others in the local community (Blamey et al. 2000; Morrison, Bennett, and Blamey 1999).

A main argument against including market impacts is that it is unnecessary as one could simply utilize market information rather than non-market valuation techniques to measure the welfare effects of job creation or losses. Furthermore, when market impacts are included in CEs, there is a risk of double counting (Diamond and Hausman 1994) or, relatedly, that respondents act as *homo politicus* rather *homo economicus* (Nyborg 2000). From a neo-classical perspective, it is not a common practice to consider the employment of others as a nonmarket benefit (Milgrom 1993). Finally, the design consideration of *simplicity* would favor exclusion rather than inclusion of market impacts in CEs.

To our knowledge, no other study has examined the consequences of including/excluding an employment attribute through a split-sample design. Nonetheless, several previous studies have included employment and/or other market impacts in the designs. As one of earliest applications of DCE in an environmental economics context, Adamowicz et al. (1998) obtain statistically insignificant preferences for forest industry employment associated with a caribou habitat-enhancement program. Examining preferences toward renewable energy investments (in Scotland), Bergmann, Hanley, and Wright (2006) report that employment is not statistically significant in estimations for the full sample. However, it is strongly significant determinant of utility in the rural sample. Reporting from the same study, Bergmann, Colombo, and Hanley (2008) find that rural respondents have a mean WTP of approximately \$2 for each job created. Longo, Markandya, and Petrucci (2008) also study preferences in a renewable energy policy context (in Bath, England). They find that the average respondent has significant positive preferences for policies leading to increased permanent employment in the renewable energy sector, with mean WTP of \$0.04 for each additional permanent job created. Similarly, Colombo, Calatrava-Requena, and Hanley (2006) examine the nonmarket benefits of soil protection programs (in Andalusia, Spain) and find that jobs created through expansion of agricultural production due to soil protection is a significant preferences determinant. In this study, mean WTP is \$0.15 for each job created by a soil protection program. Othman, Bennett, and Blamey (2004) treat the employment of others explicitly as a social attribute of various wetland management scenarios (in Malaysia). Employment is found to be a crucial factor in policy preferences with mean WTP for each percentage increase in employment of $0.26[1]. More recently, investigating WTP for water quality improvements (in the Waikato region of New Zealand), Marsh (2012) find that a job loss attribute is significant and negative at various levels, indicating people's concern for protecting jobs. The implied WTP for water quality improvement is significantly lower when jobs are at stake.

Finally, Aanesen et al. (2018) explore the local population's preferences for commercial development and coastal eco-system protection in Arctic Norway. They conclude that new jobs is the most important attribute with a mean WTP of $0.3 to $0.5 per job. This analysis also finds that rural respondents have significantly higher WTP for new jobs than urban respondents, suggesting that both use and non-use aspects of employment may be captured by this attribute.

In this paper, we follow in the footsteps of Aanesen et al. (2018) and explore the full dataset from the same DCE survey. Specifically, the full dataset includes a sub-sample of respondents who received a version of the DCE that did not include the employment attribute. Conducting a split-sample analysis affords us a unique opportunity to explore whether and how inclusion of the employment attribute affects attribute attendance and the welfare estimates of environmental attributes.[2]

Attribute non-attendance and market attributes in recent DCE studies

In order to assess the extent to which contemporary environmental DCE research has focused on the above issues, we conducted a selective sampling of the DCE studies from four prominent environmental economics journals.[3] Out of 38 articles surveyed, as many as 17 reported from a study that included some kind of market-related attribute. However, only one study included

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[1] For ease of comparison, all WTP measures presented in this section are converted into USD using the average annual exchange rate in the year of the respective research, except for Othman, Bennett, and Blamey (2004) who have provided the exchange rate RM 3.8=1 USD, which we employed for conversion.

[2] Ahi (2018) provides an exploration of the role and impact of the job-attribute, but without focusing on AN-A.

[3] The four journals were *Ecological Economics*, *Environmental and Resource Economics*, *Journal of Environmental Economics and Management*, and *Marine Resource Economics*. The sampling covered the period 2000-2018 for up to 10 DCE studies from each journal. A detailed summary is available upon request.

an employment attribute (Oviedo and Yoo 2017). Furthermore, only five articles mentioned the possibility of attribute non-attendance, with two providing explicit explorations (Meyerhoff, Oehlmann, and Weller 2015; Petrolia, Interis, and Hwang, 2018). One study did both, i.e., included a market attribute and discussed AN-A, though without drawing a connection between the two issues (Campbell, Venn, and Anderson 2018).

EMPIRICAL APPLICATION: ARCTIC COASTAL ZONE MANAGMENT

Norway faces many critical decisions regarding the use of the coastal zone and related ecosystem services with multiple ongoing conflicts between the authorities of local planning, regional fisheries, and environmental protection (Bennett 2000; Aanesen et al. 2018). The focus of this study is the Northern counties of Troms, Nordland and Finnmark, which comprise the region known as *Arctic Norway*. Decision-making processes for coastal zone management in Arctic Norway is more difficult compared to the southern parts of the country, partly due to the fact that issues related to protecting the livelihood and cultural interests of the indigenous population come into play (Jentoft and Buanes 2005). Furthermore, the region is characterized by tough climatic conditions, long distances, and low population density. Arctic Norway makes up 1/3 of the land area of Norway, but inhabits less than 10% of the population. While parts of the long coastline are more densely populated with some range of economic activities, long stretches are desolate with rather underutilized natural resources. Historically, these characteristics has led to lower rates of economic development in this region than the rest of the country. In light of these regional characteristics, the pristine nature and rich resource base of Arctic Norway deliver both opportunities and challenges. On one hand, the area is highly suitable for the development of several emerging industries including aquaculture and marine fishing tourism. On the other hand, these industries face both political and social resistance (Hersoug et al. 2017).

Following the 2014 drop in oil prices the aquaculture industry has become increasingly important for the Norwegian economy. In 2016, the Norwegian aquaculture industry produced approximately 1.3 million tons of fish (mostly farmed salmon) with sales value of approximately NOK 64 billion, up from less than NOK 30 billion in 2012 (Statistics Norway 2017). Correspondingly, the coastal areas employed in aquaculture production have started to extend from the west coast of Norway to the northern regions (Sandersen and Kvalvik 2015). However, the expansion of the industry is met with reluctance and skepticism related to various concerns over environmental impacts and negative effects on the coastal uses of other groups, including recreational and indigenous stakeholders (Hersoug 2013; Hovik and Stokke 2007; Hersoug et al. 2017).

In recent decades, remote regions of Northern Norway have become primary destinations for marine fishing tourism, especially following the government's promotion efforts in the mid-90s (Borch 2009; Solstrand 2014). However, despite the fact that the marine fishing tourism contributes to the economy of the region, weak regulations and poor environmental monitoring have resulted in stakeholder conflicts at various levels (Borch 2009; Solstrand 2013).

Finally, though the unemployment rate in Arctic Norway is currently not significantly above the national average, the Northern counties depend heavily on jobs in public sector. For this reason, the aquaculture industry and marine fishing tourism are seen as promising for expanding commercial activities and economic growth in the region. With the above as a back-drop, Arctic Norway constitutes an interesting context for studying preferences for coastal zone management, in general, and the sensitivity of DCE results to the inclusion of an employment attribute and accounting for AN-A, in particular.

The DCE survey design and data collection

The overall objective of the study was to obtain information that could facilitate improved management outcomes relating to the expansion of commercial activities on the Arctic coast. The DCE design began by seeking input from various stakeholder groups (Aanesen et al. 2018). Specifically, the initial DCE development involved four focus groups with local citizens and two focus groups with a mix of representatives from municipalities, relevant industries, and NGOs. In the focus groups, the discussions centered around the use of coastal zone for recreational and commercial purposes, and the participants expressed their opinions about the development of the marine fishing tourism and the aquaculture industry.

The participants agreed that marine fishing tourism and aquaculture are essential for the economic development of the region. However, as the locals use the coastal zone extensively for recreational activities, landscape changes were deemed relevant by many participants. They also expressed environmental concerns about the expansion of marine fishing tourism and the aquaculture industry. Particularly, increased marine and coastal litter from industrial development was a recurring theme. Another environmental aspect stressed by the participants was the possible adverse impacts on local recreational fishing, which is an integral part of the cultural traditions of Arctic Norway residents.

Based on input from the focus groups, the preliminary DCE design included the non-cost attributes of visual intrusion introduced by marine fishing tourism and the aquaculture industry, increased beach littering, reductions in the recreational fishing harvest of the locals, and new jobs created by marine fishing tourism and aquaculture industries. As the focus groups rejected the idea of introducing a fee for recreational use of the coastal zone, the payment vehicle deemed most feasible and consequential was an increase in the annual household tax paid to local authorities. A preliminary DCE consisting of these attributes was subsequently tested and modified through additional focus groups and one-on-one interviews.

A pilot test was then implemented for investigating whether the policy context is realistic, and the choice tasks are comprehensible. The pilot survey utilized a d-efficient design with zero priors. The pilot data collection took place in August 2015 with 100 respondents, and the choice card design went under minor modifications based on the feedback. The parameter estimates obtained from the pilot study further served as priors for generating a d-efficient design for the final DCE. Both the pilot and main DCE designs were generated using the NGene software (Choicemetrics 2014).

The data collection was implemented in September 2015 as a web-survey using the pre-recruited household panel of a major survey sampling company in Norway. The data collection process used a randomized split-sampling scheme, with one sub-sample receiving the employment attribute, while the other sub-sample did not see this attribute. The survey treatments were identical in all other aspects for the two sub-samples. The survey was available online for about a month. By the closing date, there were 490 and 518 respondents for the no-job version and job version, respectively, yielding an overall response rate of approximately 47%.

The final, full DCE design included the following attributes: 1) recreational catches (HARVEST), 2) impact on views due to development of aquaculture and marine fishing tourism (SCENIC), 3) beach litter (LITTER), 4) new jobs created by industrial development (JOBS), and 5) change in annual household tax payments (COST). Table 1 presents s summary of the experimental design, while Figure 1 presents a choice card example. The business-as-usual (BAU) alternative represents *unrestricted* commercial development along the coast and, therefore, is associated with the most adverse environmental impacts as well as the highest number of jobs created. The other alternatives represent management scenarios with stricter regulations resulting in fewer environmental impacts and jobs. All participants responded to eight choice cards, each containing these three alternatives.

INSERT FIGURE 1 APPROXIMATELY HERE

As the descriptive statistics in Table 2 indicate, the two sub-samples are virtually identical in terms of their socio-economic profiles. Hence, any difference in results across the two sub-samples is likely to be attributable to the design version, not differences in the underlying characteristics of the survey participants.

INSERT TABLE 2 APPROXIMATELY HERE

ANALYTICAL FRAMEWORK

DCE analysis is typically motivated from a discrete choice random utility model (RUM), framework. According to the RUM, total utility (U) consists of a systematic component, V, to be estimated parametrically, and a stochastic component, ε (McFadden 1974; Train 2009). Total utility from alternative j faced by individual n on choice occasion t is expressed as:

$$U_{jnt} = V_{jnt} + \varepsilon_{jnt} = \beta x_{jnt} + \varepsilon_{jnt} \tag{1}$$

where the deterministic part of the utility (V_{jnt}) is expressed as a linear function of a parameters (β) and attribute levels (x_{jnt}). The error term (ε_{jnt}) is typically assumed to follow a type-I extreme value distribution with an expected value of zero and constant variance, which leads to standard logistic probability expressions. Specifically, the probability that alternative i is chosen over any other available alternative by individual n on choice occasion t is given by:

$$\mathrm{Pr}_{int} = \frac{\exp(V_{int})}{\sum_j^J \exp(V_{jnt})} \tag{2}$$

In our analysis, we estimate and compare results from two types of econometric models, 1) panel mixed logit (MIXL) and 2) AN-A latent class mixed logit (LC-MIXL). The MIXL model is a powerful and sophisticated approach to analyzing discrete choice data due to fact that it accounts for multiple-observations per respondent, permits preference heterogeneity, and relaxes the independence of irrelevant alternative (IIA) assumption of the standard conditional logit model. The joint MIXL probability for the sequence of individual *n*'s preference expressions (y_n) over *J* alternatives on *T* choice occasions is given by:

$$\text{Prob}(y_n|\theta) = \int \prod_{t=1}^{T} \frac{\exp(V_{int})}{\sum_j^J \exp(V_{jnt})} f(\beta|\theta) d\beta \quad , \tag{3}$$

where $f(\beta|\theta)$ represents the distribution of random parameters (β) characterized by a set of coefficients to be estimated (θ); see Train (2009) for further technical details.

A limitation of the MIXL approach, which has been pointed out in recent research (e.g., Lew, 2019), is that it does not explicitly account for AN-A. In contrast, the LC-MIXL model, first proposed by Hess et al. (2013), is a flexible way of exploring the AN-A phenomenon. It combines discrete and continuous mixing distributions. Firstly, it allows for any pattern of AN-A, from non-attendance to single attributes to non-attendance to sub-sets of attributes (e.g., pairs, triplets, all non-cost attributes, etc.), through latent class specifications. There are 2^K classes in a complete specification, where K is the number of potentially non-attended attributes. Secondly, the model distinguishes, probabilistically, between zero attribute weights associated with non-attendance (potentially due to choice task complexity and response heuristics) and near-zero attribute weights due to low preference intensities. It achieves this by incorporating a random parameter distribution in the same fashion as the MIXL model. The LC-MIXL likelihood function for respondent *n* is given by:

$$\text{L}(y_n|\theta, \boldsymbol{\pi}) = \sum_{s=1}^{S} \pi_s \int \prod_{t=1}^{T} P(i_{nt}^*|\beta_s = \beta^\circ\Lambda) f(\beta|\theta) d\beta \tag{4}$$

Here, π_s is the latent class membership probability, i_{nt}^* is the indicator for the alternative chosen by the individual *n* on choice occasion *t*, and Λ represents a matrix specifying combinations of zero and non-zero elements for the S = 2^K different attendance classes. With an assumption of independent AN-A behavior across attributes, the model requires estimation of only K number of AN-A probabilities, instead of estimating the whole set of 2^K -1 probabilities (Hole 2011). Therefore, the modeling of π under AN-A assumption implies that $\pi_k^0 + \pi_k^1 = 1$, where π_k^0 and π_k^1 represent non-attendance and attendance probabilities for attribute k, respectively (Sandorf, Campbell, and Hanley 2017). In the given setting, the probability of observing an AN-A combination s which consists of attendance for attributes 1 and 2 and AN-A for attributes 3 and 4 becomes the product of each membership probability: $\pi_s = \pi_1^1 \times \pi_2^1 \times \pi_3^0 \times \pi_4^0$ (Erdem, Campbell, and Hole 2015).

Relating equation (1) to the DCE attributes of our application context, we specify the following deterministic indirect utility for the job sub-sample:

$$V_{int} = \alpha_{SQ} + \beta_1 SCENIC_{int} + \beta_2 LITTER_{int} + \beta_3 HARVEST_{int} + \beta_4 JOBS_{int} + \beta_5 COST_{int} \quad (5)$$

For the no-job sub-sample, $\beta_4 = 0$ by design. We apply Hess et al.'s (2013) LC-MIXL framework for identifying the AN-A patterns for both sub-samples, where the 2^K LC-MIXL model result in 32 and 16 classes of AN-A combinations for the jobs and no-jobs subsamples, respectively. Following the specification in Aanesen et al. (2018), we adopt a multivariate normal distribution for the non-cost attribute parameters (*SCENIC*, *LITTER*, *HARVEST*, and *JOBS* for one sub-sample) in order to permit a wide range of preference heterogeneity, while we treat the COST parameter as fixed. Apart from the ease of interpretation and significant reduction in simulation time, fixing the COST attribute also ensures that the distribution of marginal WTP becomes simply the distribution of the non-cost attribute's coefficient (e.g., Carlsson, Frykblom, and Liljenstolpe 2003). This simplification has both economic and statistical appeal as this study focuses primarily on changes in WTP measures. Deviating from the specification in Aanesen et al. (2018), we also include the alternative-specific BAU constant (α_{SQ}) in the set of random parameters. This accounts for potential heterogeneity in attitudes towards the current situation, which may influence AN-A behavior.[4]

Neither model (3) nor model (4) have a closed-form solution. Hence, they must be must approximated through simulated maximum likelihood estimation. All models presented below are estimated by making appropriate adaptations/modifications to the R package Apollo (Hess and Palma 2019), with each employing 1000 scrambled Sobol draws for simulation.[5]

ESTIMATION RESULTS

Table 3 summarizes the main results from the MIXL and LC-MIXL estimations for the two sub-samples. The signs of the *mean* coefficients indicate that preferences are qualitatively stable across the four estimations. However, the relative magnitudes of the *standard deviation* coefficients highlight significant taste heterogeneity in the population through all attributes. Most of the *mean* and *standard deviation* coefficients for the random parameters are significant at 1% level. Exceptions are the mean SCENIC coefficient in the LC-MIXL JOBS estimation and the mean HARVEST coefficient in the LC-MIXL NO JOBS estimation.

INSERT TABLE 3 APPROXIMATELY HERE

Overall, the estimations show that respondents tend to prefer alternatives with stricter regulation over the current situation. Furthermore, they prefer having both industries expand on

[4] The SCENIC attribute is an indicator for expanded presence of both marine tourism fishing and aquaculture industry, with the reference level being expansion of only one of these industries. The other three attributes are entered quantitatively according to Table 1, i.e., as increase in beach litter (LITTER), reduction in recreational catch (HARVEST) and creation of new jobs in the community (JOBS).

[5] We employ scrambled Sobol draws following recent research by Czajkowski and Budziński (2019), which demonstrate that such draws perform best for achieving lowest errors in DCE simulations.

the coast instead of only one, less recreational fishing catch, more jobs in the community, and less litter on the beaches.[6] As expected, the cost attribute enters negatively and highly significant in all models. An interesting pattern that emerges in the models is the enlargement of the cost attribute's coefficient as we move from full-attendance models (MIXL) to AN-A models (LC-MIXL), which implies greater cost sensitivity when non-attendance is accounted for. Previous research in the AN-A field has mixed results regarding the substantial changes in coefficient size. However, there are examples of notable increases in cost coefficient's size when switching from full-attendance models to AN-A models (e.g., Erdem, Campbell, and Hole 2015; Hensher and Greene 2010). In line with prior research conducting similar model comparisons (e.g., Hess et al. 2013; Sandorf, Campbell, and Hanley 2017), the log-likelihood gains and AIC criterion indicate that the LC-MIXL models outperform the MIXL models.

Probability of non-attendance to attributes

Table 3 also reports AN-A shares from the LC-MIXL estimations. The probability of non-attendance is relatively high, with AN-A shares ranging from 31% to 63% across sub-samples and attributes. The lowest AN-A share (31%) is associated with COST in the job sub-sample, while the highest share (63%) is associated with SCENIC in the no-job sub-sample. These statistically estimated (or "inferred") AN-A shares are corroborated by stated attribute importance statistics from DCE survey debriefing questions. For example, approximately 69% (85%) of the respondents in the no-job sub-sample indicated that visual impacts from aquaculture (marine fishing tourism) is not important to them. The discovery of substantial AN-A is also comparable to that of a previous study in similar Norwegian environmental valuation context by Sandorf, Campbell, and Hanley (2017). These authors estimate AN-A shares

[6] The negative sign on HARVEST coefficient may seem counter-intuitive. However, as explained in Aanesen et al. (2018), reduced recreational fishing catch appears to have been interpreted as a fishery protection measure by many respondents, rather than as a constraint on one's own recreational fishing opportunities.

between 23% and 62% (for all but one attribute) in a study on cold water corals in Arctic Norway.

Regarding attendance to the additional employment attribute, we observe that AN-A is relatively low for JOBS at 33%. Similarly, the cost attribute, which is essential for the identification of welfare measures, is the attribute with lowest AN-A share, and therefore, highest implied attendance share, in both sub-samples.

Finally, we observe that the AN-A shares appear to be lower in the job sub-sample. This is quite surprising as it suggests that the additional attribute helped draw attention *towards* rather than *away from* the other attributes. However, none of these differences are statistically significant according to the results obtained from a complete combinatorial convolution test (Poe, Giraud, and Loomis 2005).[7]

Welfare Measures

Similar to Aanesen et al. (2018), we examine the welfare effects associated with having both industries on the coast (SCENIC), more beach litter (LITTER), reduction in the recreational fishing catch (HARVEST) and new jobs (JOBS). Table 4 summarizes mean WTP across the two estimation models and the two sub-samples. Note that WTP estimations from the LC-MIXL models make use of only the respondents who have attended both the non-cost and cost attributes. Overall, the results indicate that the preferences for the LITTER attribute appear to be more robust across models and sub-samples in comparison to preferences for other attributes.

INSERT TABLE 4 APPROXIMATELY HERE

We first turn our attention to whether the inclusion of the employment attribute leads to differences in the welfare measures of the environmental attributes (SCENIC, HARVEST,

[7] For results of the convolution tests, please see Appendix A1.

LITTER). The results are mixed. In the MIXL models, the WTP estimates for SCENIC and HARVEST decrease by a magnitude of 37% and 55%, respectively, while the WTP for LITTER increases (becomes more negative) by approximately 9%, in presence of the JOBS attribute. In contrast, the LC-MIXL models indicate higher WTP for the establishment of both industries on the coast, with more moderate welfare measures for HARVEST and LITTER in the job sub-sample.

Next, we investigate the impact of accounting for AN-A. We observe drastic differences in mean WTP between the MIXL and the LC-MIXL models. In the no-job sub-sample, WTP for SCENIC is lowered by 98%, followed by a reduction of 93% in WTP for HARVEST when AN-A is incorporated. In contrast, the welfare measure for LITTER is larger (more negative) in the LC-MIXL specification, where the results illustrate a relatively milder change of 26%.

In the job sub-sample, we observe significant reductions in all welfare measures when we switch from a MIXL to an LC-MIXL specification. The WTP for environmental attributes of SCENIC, LITTER, and HARVEST decrease by a magnitude of 64%, 34%, and 102%, respectively. Along with the notable decline in WTPs for environmental attributes, the LC-MIXL further exhibits a substantial decrease of 95% in WTP for new jobs.

We formally test whether the differences in estimated mean WTPs across sub-samples and models are statistically significant by applying the complete combinatorial convolution test suggested by Poe, Giraud, and Loomis (2005). All the p-values obtained from the convolution tests are smaller than 0.01.[8] Consequently, we find strong evidence that both the inclusion of an employment attribute and accounting for AN-A impact welfare measures.

[8] For details on WTP differences and results of the convolution tests, please see Appendix A2.

DISCUSSION AND CONCLUDING REMARKS

The DCE design procedure involves challenging trade-offs between the simplicity and saliency of the choice sets. This paper utilized data from a split-sample DCE to investigate the impact of including an employment attribute on the locals' stated preferences for protecting the coastal zone of Arctic Norway. Specifically, we set out to investigate four research questions. 1) How large is the share of respondents attending to the employment attribute when it is included? 2) How does inclusion of the employment attribute affect AN-A for the other attributes? 3) How do WTP estimates for environmental attributes compare across the two sub-samples? 4) How do WTP estimates compare between models that incorporate AN-A relative to models that do not?

With regard to the first research question, the analysis indicates that non-attendance to the employment attribute is relatively modest, and in line with the AN-A rates for the other attributes. Furthermore, this attribute is statistically significant with economically significant welfare estimates. The local population appears to have strong preferences for regional jobs, consistent with findings in several previous studies (e.g. Longo, Markandya, and Petrucci 2008; Marsh 2012; Othman, Bennett, and Blamey 2004).

With regard to the second research question, inclusion of the employment attribute does not appear to draw attention away from the other attributes. In fact, while not statistically significant, the AN-A rates are lower in the job sub-sample estimation than in the no-job sub-sample estimation. Importantly, attention towards the cost attribute is not adversely affected by the additional attribute dimension. This is re-assuring for the identification of welfare measures in AN-A models, as the cost parameter plays a crucial role in monetizing incremental utilities associated with non-cost attributes.

With regard to the third research question, we found mixed results for the impact on scenic views (SCENIC) and beach litter (LITTER), while the welfare estimates were smaller for recreational fishing catch (HARVEST) when the employment attribute (JOBS) was included.

Regarding the fourth research question, we found that controlling for AN-A (in the LC-MIXL models) seems to reduce welfare measures (compared with results from the MIXL models). This finding is consistent with observations made in prior AN-A research (e.g., Campbell, Hensher, and Scarpa 2011; Scarpa et al. 2012; Hess et al. 2013).

In general, we believe that our analysis has provided a valuable empirical exploration of the A-NA phenomenon by simultaneously studying the implications of including an employment attribute in the DCE designs, or more generally, increasing DCE complexity (Hensher 2006a; Hensher 2006b; Weller et al. 2014). We refrain from making a judgement as to which design or estimation strategy is correct, that is, which empirical approach is most likely to reveal the "true" environmental preferences of people. However, given the differences in welfare measures across sub-samples and estimation models uncovered by our analysis, more research in this area is clearly warranted. For policy analysis and public management, the choice of welfare estimates clearly matters for environmental outcomes.

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FIGURE 1: Sample Choice Card (with employment attribute version)

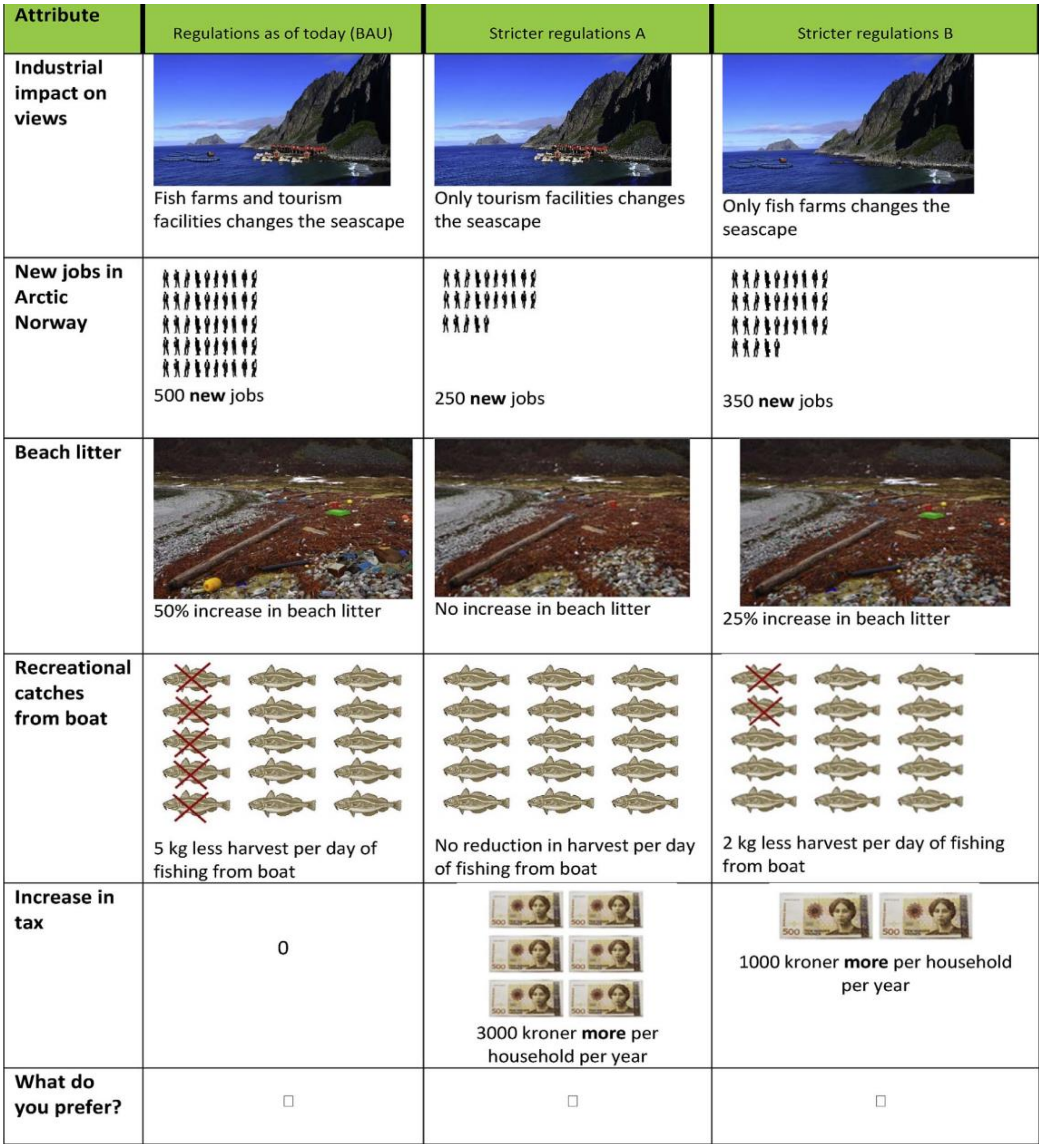

Table 1: Attributes and levels

Attribute	BAU Level	Level 1	Level 2	Level 3	Level 4
Industrial impacts on view	Aquaculture and marine fishing tourism	Only aquaculture	Only marine fishing tourism		
Litter	50% increase compared to the current situation	25% increase compared to current situation	No increase in litter		
Recreational catches	Daily catches (15 kg) reduced by 5 kg	Daily catches (15 kg) reduced by 2 kg	No reduction from daily catches (15 kg)		
New jobs	500 new jobs in Arctic Norway	350 new jobs in Arctic Norway	250 new jobs in Arctic Norway	100 new jobs in Arctic Norway	
Costs (NOK)	0	500	1000	2000	3000

Table 2: Demographics of the two subsamples.

Demographics	Jobs Sub-Sample (n=518)	No-Jobs Sub-Sample (n=490)
Male	45%	51%
Age	49	51.1
University degree and above	60%	64%
Member of recreational organization	18%	19.2%
Member of environmental organization	6%	6.7%
Annual household income NOK400K-599K	19.1%	19.4%
Annual household income NOK600K-799K	21%	23%
Annual household income NOK800K-999K	24%	20%
Full-time employee	51.2%	51.8%
Student	8.9%	7.1%
Retiree	20.5%	21.4%

Table 3: Mixed logit estimation results.

	MIXL NO JOBS		MIXL JOBS		LC-MIXL NO JOBS		LC-MIXL JOBS	
	Mean (s.e.)	SD (s.e.)	Mean (s.e.)	SD (s.e.)	Mean (s.e.)	SD (s.e.)	Mean (s.e.)	SD (s.e.)
BAU	-0.17**	-3.02***	-0.57***	-2.0***	-4.81***	11.77***	-2.23***	9.22***
	(0.09)	(0.11)	(0.08)	(0.06)	(0.49)	(0.92)	(0.27)	(0.7)
SCENIC	0.99***	-2.53***	0.44***	1.11**	0.13	1.09***	2.04***	2.29***
	(0.08)	(0.10)	(0.07)	(0.04)	(0.13)	(0.18)	(0.33)	(0.22)
LITTER	-1.19***	4.04***	-0.93***	1.55***	-13.86***	-14.25***	-7.26***	8.68***
	(0.10)	(0.15)	(0.08)	(0.05)	(1.25)	(1.21)	(0.88)	(0.85)
HARVEST	3.08***	3.71***	0.97***	1.87***	1.73***	6.9***	-0.33	4.54***
	(0.13)	(0.13)	(0.06)	(0.06)	(0.51)	(0.6)	(0.3)	(0.44)
COST	-0.59***	-	-0.47***	-	-5.45***	-	-5.68***	-
	(0.02)		(0.01)		(0.1)		(0.48)	
JOBS	-	-	1.04***	1.40***	-	-	0.70***	1.92***
			(0.04)	(0.05)			(0.15)	(0.15)
Prob. AN-A SCENIC	-	-	-	-	0.63***	-	0.51***	-
					(0.04)		(0.06)	
Prob. AN-A LITTER	-	-	-	-	0.58***	-	0.55***	-
					(0.03)		(0.04)	
Prob. AN-A HARVEST	-	-	-	-	0.48***	-	0.35***	-
					(0.05)		(0.05)	
Prob.AN-A COST	-	-	-	-	0.44***	-	0.31***	-
					(0.02)		(0.05)	
Prob. AN-A JOBS	-	-	-	-	-	-	0.33***	-
							(0.05)	
LL (0)	-19351		-20254.05		-19351		-20254.05	
Log-likelihood	-6735.8		-7495.9		-5187.6		-5526.2	
AIC	13489		15013		10414.6		11103.6	
N	450		471		450		471	

Table 4: Mean marginal WTP and 95% confidence intervals (in Norwegian Kroner)

ATTRIBUTE	MIXL NO-JOB	MIXL JOB	LC-MIXL NO-JOB	LC-MIXL JOB
SCENIC	1608	1018	24	362
	1525, 1691	968, 1067	20, 29	355, 373
LITTER	-1980	-2152	-2499	-1418
	-2039, -1777	-2223, -2081	-2552, -2440	-1437, -1365
HARVEST	5120	2280	326	-49
	4998, 5242	2196, 2365	301, 353	-66, -31
JOBS	-	2400	-	122
	-	2337, 2464	-	110, 134

NOTES: All estimates are reported on an annual per household basis. (1 NOK = \$0.11). The WTPs reflect the welfare associated with having both industries on the coast (SCENIC), 100% increase in beach litter (LITTER), per kilogram reduction in recreational harvest (HARVEST) and per 100 new jobs (JOBS).

Appendix A1: Significance test for differences in AN-A shares

AN-A Shares	LC-MIXL NO-JOB	LC-MIXL JOB	DIFFERENCE	P-VALUE
SCENIC	0.63	0.51	0.12	0.46
LITTER	0.58	0.55	0.03	0.49
HARVEST	0.48	0.35	0.13	0.44
COST	0.44	0.31	0.13	0.45

Note: P-values computed by complete combinatorial convolution test by Poe, Giraud, and Loomis (2005).

Appendix A2: Significance tests for difference in mean welfare estimates.

Models	SCENIC		LITTER		HARVEST		JOBS	
	WTP difference	p-value	WTP difference	p-value	WTP difference	p-value	WTP difference	p-value
MIXL No-Job vs. MIXL Jobs	NOK 590	0.00	NOK 172	0.00	NOK 2840	0.00	-	-
LC-MIXL No-Job vs. LC-MIXL Jobs	NOK 338	0.00	NOK 1081	0.00	NOK 375	0.00	-	-
MIXL No-Job vs. LC-MIXL No-Job	NOK 1584	0.00	NOK 519	0.00	NOK 4794	0.00	-	-
MIXL Jobs vs LC-MIXL Jobs	NOK 656	0.00	NOK 734	0.00	NOK 2329	0.00	NOK 2278	0.00

Note: P-values computed by complete combinatorial convolution test by Poe, Giraud, and Loomis (2005). The unit changes are presented in absolute value.